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MARNIK G. DEKIMPE, PHILIP M. PARKER, and MIKLOS SARVARY*

The authors propose a new methodology called the "coupled-hazard approach" to study the global diffusion of technological innovations. Beyond its ability to describe discontinuous diffusion patterns, the method explicitly recognizes the conceptual difference between the timing of a country's introduction of the new technology (the so-called implementation stage; Rogers 1983) and the timing of the innovation's full adoption in the country (the confirmation stage). To illustrate the method, the authors apply it to the global diffusion of digital telecommunications switches across more than 160 countries.

Global Diffusion of Technological Innovations: A Coupled-Hazard Approach

As the globalization of markets increases, managerial interest in understanding adoption processes across countries has led to calls for more academic research on international diffusion (see, e.g., Douglas and Craig 1992). Although several studies have begun to answer this call, attention has mainly focused on a comparison of within-country diffusion patterns of consumer durables across a limited number of industrialized countries.[1] This article is the first to consider the global diffusion of a particular type of innovations, namely, those relying extensively on technological advancements (computers, software, telecommunications innovations, and the like).

Several factors make the study of global technology diffusion particularly interesting as well as challenging. In particular, we focus on three key issues: (1) the two-stage nature of the global diffusion process, (2) the potential irregularity of the resulting diffusion pattern due to the presence of network externalities and/or central decision makers, and (3) the role of the installed base of older generation technologies that the innovation replaces.

First, we argue that global adoption comprises two stages (as defined by Rogers 1983), which are conceptually different (but related) measures of innovativeness across countries:

- the time between an innovation's first availability in the world and its first appearance in a country, that is, the *implementation stage*, and
- the time between the innovation's initial trial in a country and its full adoption or substitution, that is, the *confirmation stage*.

From a managerial perspective, both aspects may influence production and/or marketing planning decisions. For example, the likely adoption or trial date for some countries may lie well beyond the firm's typical planning horizon. Similarly, when the initial adoption decision has been made, managers become interested in the subsequent speed of diffusion of the new technology in that country, that is, how long it will take the country to replace the old technology fully. Although the implementation and confirmation stages address separate managerial problems and represent two conceptually different diffusion processes (potentially involving different decision makers and word-of-mouth processes), they should not be studied independently. Indeed, these two processes are closely interlinked and may influence one another. For example, countries trying the innovation later may reach full confirmation sooner if they can benefit from previous adopters' experiences with the technology.

Second, although all global products diffuse in the manner theorized previously, technological innovations such as computers or telecommunications products tend to have unique characteristics as compared with other industrial or

[1]Gatignon, Eliashberg, and Robertson (1989) and Mahajan and Muller (1994), for example, compare Bass's (1969) diffusion parameters for several household appliances across a set of European countries. Takada and Jain (1991) compare these diffusion parameters for four Pacific Rim countries, and Helsen, Jedidi, and DeSarbo (1993) assess similarities in the diffusion of three consumer durables across 12 industrialized countries. In a recent article involving 10 European countries and four durable products, Putsis and colleagues (1997) provide an innovative model of diffusion across countries, describing the mixing behavior of heterogeneous populations.

*Marnik G. Dekimpe is Associate Professor of Marketing, Catholic University Leuven (e-mail: marnik.dekimpe@econ.kuleuven.ac.be). Philip M. Parker is Professor of Marketing, INSEAD, and Professor of Economics and International Strategy, UCSD (e-mail: parker@insead.fr). Miklos Sarvary is Assistant Professor of Business Administration, Harvard Business School (e-mail: msarvary@hbs.edu). The authors are listed alphabetically. They are indebted to Frenkel ter Hofstede, "Seenu" V. Srinivasan, and Jan-Benedict E.M. Steenkamp for their insightful comments and to Marie-Louise Berry, William Fisk, Katrijn Gielens, Eva Szekeres, and Hagit Zeev for their excellent research support. To interact with colleagues on specific articles in this issue, see "Feedback" on the *JMR* Web site at www.ama.org/pubs/jmr.

Table 1
ADOPTION TIMING OF THE NEW TECHNOLOGY: AN EXAMPLE

Country	t_1	t_2	t_3	t_4
C_1	0	100	100	100
C_2	10	20	40	80
C_3	100	100	100	100
C_4	0	0	10	20

Notes: Figures indicate the percentage of the old technology replaced by the new one. A nonzero number indicates trial (implementation), whereas full adoption (confirmation) is reflected by 100%.

consumer goods. In particular, they often exhibit "network externalities" (Katz and Shapiro 1985), in which consumers benefit from other consumers' use of a product based on the same technology. The existence of network externalities requires increased coordination of consumer adoptions because, the technology's value depends on the total size of the adopter population. Network externalities often result in the imposition of a standard or of special regulations on users (Economides 1996). As a result, the diffusion path of the new technology may occur in blocks or packets, which makes the diffusion process discontinuous. The need for increased consumer coordination and the setting of standards or regulations also means that, beyond individual consumers' adoption decisions, the diffusion process of technological innovations is typically influenced to some extent by central decision makers, especially in the early stages of the diffusion process.[2] For telecommunications innovations, for example, the local PTT (posts, telegraphs, and telephones) or the government (in European countries) or the Federal Communications Commission (in the United States) acts as a key decision maker in setting standards and regulations, which in turn influence the product's diffusion path, especially in the implementation stage. As such, heterogeneity across countries in the role, influence, and power of these central agencies might result in vastly different diffusion patterns. In some countries, especially small ones, for example, the central decision-making unit might decide to replace the old technology fully with a new one at the trial stage, which would make the implementation and confirmation stages indistinguishable.

We illustrate this problem in Table 1, which gives four diffusion scenarios. For country C_1, the implementation and confirmation stages cannot be distinguished. In the case of digital communication switches, for example, Gabon, Gambia, and Jamaica implemented digital technology ubiquitously within their first year of adoption. This type of adoption behavior (100% penetration in the first year) runs counter to the notion that adoption patterns in every social system follow an S-shaped penetration curve. Whereas some countries reach full penetration at the moment of adoption, others exhibit a diffusion pattern that resembles the familiar S-shaped adoption pattern (e.g., country C_2 in Table 1). In the same working example, this was the case for countries such as France, Finland, Hong Kong, and the Dominican Republic, which maintained a mixture of digital and analogue telecommunications networks for several years after their initial trials of the newer digital technology. It should be noted that both forms of within-country diffusion (i.e., instantaneous versus gradual substitution) can occur for both innovative (early-trial) and laggard (late-adopter) countries, as is illustrated by countries C_3 and C_4 in Table 1. Again in the digitization example, Gabon and Gambia went to immediate full substitution in 1987, whereas the Maldives did so in 1991. As for the gradual substitution, France started the process in 1981, whereas Israel initiated the process only eight years later. As such, a global diffusion model for technological innovations must simultaneously accommodate and explain a wide variety of (continuous and discontinuous) within-country diffusion patterns and should capture variations in both the starting time of the diffusion process and the subsequent diffusion path.

New technological innovations often complement or modify existing ones that themselves have already undergone, or are still undergoing, a diffusion process. Examples include the substitution of analogue telephone switches with digital ones and the evolution of computer standards over time. As Norton and Bass (1987, 1992) illustrate, both diffusion processes are interlinked, raising the questions (1) whether the old technology will be fully replaced by a newer generation and (2) how the size of the old technology's installed base will affect the speed of diffusion of the new generation. We explicitly consider the substitution issue and measure the impact of the old technology's installed base on both stages in the international diffusion process.

We develop a coupled-hazard model, which can incorporate all aspects of the global diffusion process of technological innovations we have mentioned. In particular, in addition to being flexible enough to test various research hypotheses, the proposed approach can distinguish clearly between the different stages of the global diffusion process and quantify the link between them. Furthermore, it can accommodate irregular diffusion patterns by allowing full adoption in the first year for some countries and gradual adoption in others. Finally, it enables us to estimate the impact of the old technology's installed base on the diffusion process of the new technology. In the next step, we illustrate the method using data on the timing of digital telecommunications network implementation (first digital system installation) and full substitution (replacement of all analogue systems by digital systems in a given country) across the global marketplace. We consider more than 160 countries located across all continents: 51 in Africa, 38 in Asia, 37 in the Americas, 27 in Europe, and 9 in Oceania.[3] In this context, we generate substantive insights with respect to four general factors of theoretical interest for global diffusion: (1) economic, (2) social/demographic, (3) installed base, and (4) international experience factors. In doing so, we identify characteristics that enable researchers and managers to distinguish between countries along Rogers's (1983) "innovator–laggard" continuum, and we quantify the differential impact of these characteristics on the subsequent speed of diffusion after initial trial.

We first present a theoretical framework and related research hypotheses. Next, we present the coupled-hazard

[2]We thank one of the reviewers for drawing our attention to this issue.

[3]Countries are defined broadly, in that they also include territories, protectorates, colonies, and United Nations members that are, however, often represented as 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., Puerto Rico).

modeling approach. Throughout the model presentation, we refer to the digitization of telecommunications services as a working illustration. After the model discussion, we turn to the empirical findings. We conclude with caveats and suggestions for further research.

THEORETICAL FRAMEWORK

Using hundreds of studies in various disciplines (e.g., sociology, education, marketing, economics) as a basis, Rogers (1983, p. 10) defines diffusion as the adoption of an innovation "over time among the members of a social system." Each individual in the social system is thought to go through four stages of adoption: awareness, interest/intention, implementation, and confirmation. We seek to extend diffusion theories to explain the implementation and confirmation stages, during which diffusion takes place across the different countries of the world, that is, when the community of nations is the social system of interest. The awareness and interest stages are difficult to measure directly and may become increasingly invariant across countries because of the emergence of the information age. In other words, all countries and governments can be assumed to know of a given innovation shortly after its discovery or invention. In the telecommunications industry, for example, all countries are members of the International Telecommunications Union, which regularly reports the existence of innovations to governments.

The Implementation Stage

In contrast to previously published studies that focus on a comparison of within-country diffusion parameters based on Bass's (1969) model, we first want to understand the forces driving the start of a country's diffusion process, which logically precedes any subsequent comparison of penetration levels. The great variability in the trial time of digital communication systems, for example, is illustrated in Figure 1. The figure shows both the actual number of countries introducing digital technology in a given year and the number of adopters predicted by Easingwood, Mahajan, and Muller's (1983) aggregate diffusion model. The figure displays the familiar bell-shaped diffusion pattern. Although it gives a parsimonious description of how fast the innovation will be accepted across the world, it does not help management understand why certain countries adopt sooner than others. Indeed, the aggregate diffusion model used to make the forecasts ignores differences among countries and cannot explain why in a given year some countries have a higher probability of adopting than others.

Micro-level models relax this homogeneity assumption and allow a heterogeneous probability of adoption across potential adopters (Chatterjee and Eliashberg 1990; Sinha and Chandrashekaran 1992). Moreover, because the unit of analysis is at the individual level, various causal factors that may affect the individual adoption decision can then be included directly into the model and formally tested. In our context, the individual-level hazard model we use will help classify countries along Rogers's innovator–laggard spectrum and answer the question, Does the profile of an innovative country differ from that of a laggard country, and if so, what are the distinguishing features?

The Confirmation Stage

As indicated by Rogers (1983), the decision to try a new technology is not necessarily the terminal stage in the innovation decision process. During the confirmation stage, the decision-making unit seeks additional information or experiences the relative performance of the new technology, after which it may decide to accelerate, discontinue, or even reverse the diffusion process. As discussed previously, this second stage can also be characterized by a substantial amount of variability across countries. Beyond explaining the trial phase of the diffusion process, the coupled-hazard model simultaneously enables us to understand what forces affect the rate at which different countries reach full confirmation, as reflected in full substitution of the old technology by the new one.

Diffusion Patterns

For most innovations, the adoption process of each country starts with the implementation stage, which is followed by the confirmation stage, and each stage takes up a finite amount of time. However, for technological innovations, as a result of network externalities and/or the involvement of central decision makers, within-country diffusion might be instantaneous, and as such, the confirmation stage of certain countries may have zero duration.[4] Thus, we can observe two broad adoption patterns. In one, a country first tries the innovation partially and reaches full adoption gradually. In the other, the country reaches full adoption immediately at the time of trial.

To describe the underlying dynamics of the resulting diffusion patterns, it is important to realize that, at any given time, each country will be in one of the following three (exhaustive and mutually exclusive) states (see Figure 2): State [0,0], in which each country starts and in which it stays as long as it has reached neither trial nor full confirmation; State [1,0], when a country has partially adopted the innovation (i.e., when the confirmation stage is still incomplete); and State [1,1], when the innovation has fully replaced the old technology. Diffusion occurs when countries move from one state to another, and these movements between the different states are described through three transition rates: r_1 (from [0,0] to [1,0]), r_2 (from [0,0] to [1,1]), and r_3 (from [1,0] to [1,1]). Each of these rates reflects a conceptually different process and may be driven by different considerations. For example, the size of the installed base of the old technology may be an important consideration in the decision to replace the old technology fully, thereby affecting r_2 and r_3, but could be less of a factor in the decision to try the new technology on a limited scale (r_1). Alternatively, for a country in State [1,0], its own experience with the new technology may be an important determinant for the speed with which it will achieve full substitution (r_3), whereas a country in State [0,0] can only rely on other countries' experiences for its decision whether and when to move to State [1,0] (r_1) or [1,1] (r_2).

We therefore frame the different research hypotheses in terms of the three transition rates in Figure 2. For the implementation stage, we are interested in the arrows leaving State [0,0], whereas for the confirmation stage, we focus on the arrows entering State [1,1], which explains the conceptual linkage between the two diffusion stages (the implementation and confirmation stages) and the three transition rates in Figure 2. As discussed in more detail subsequently,

[4]The temporal aggregation of the observed penetration level may be another factor contributing to an instantaneous confirmation stage (i.e., the diffusion process within the first interval is not observed).

the overall trial or implementation rate is then given by the sum of r_1 and r_2, whereas the confirmation rate is allowed to exhibit state dependence, in that the rate at which State [1,1] is entered can vary depending on the state currently occupied by the country, that is, State [0,0] or State [1,0].

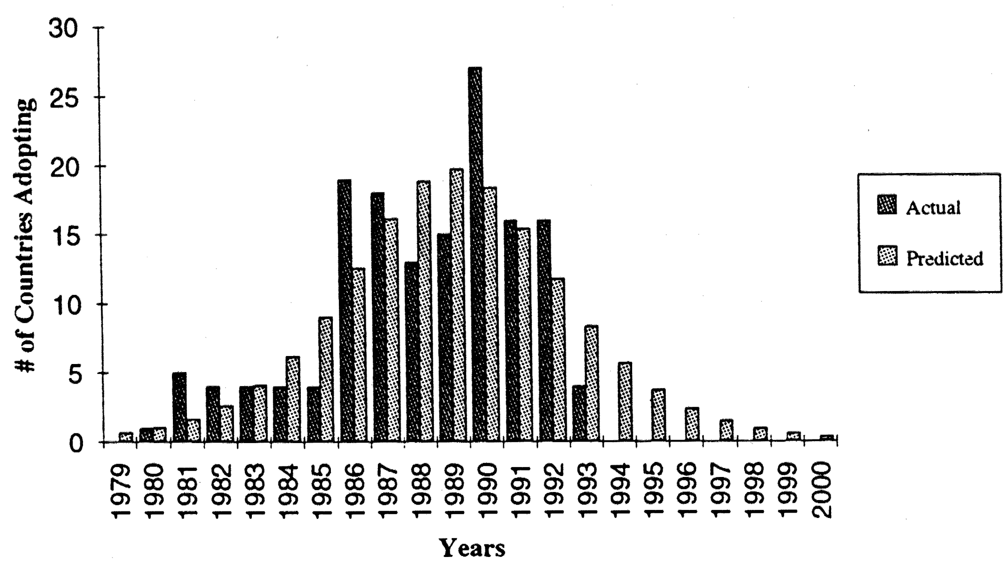
Research Hypotheses

Given our conceptualization, our goal is to gain insights into how country characteristics affect the three transitions described previously: (1) reaching partial adoption, (2) reaching immediate full substitution, and (3) reaching full substitution after partial trial. To do so, we extend diffusion theory to the global theater by considering four theoretical factors: (1) economic, (2) social/demographic, (3) installed-base, and (4) international experience factors. Although many of our hypotheses are applicable to innovations in general, some consider special characteristics of technological innovations, as is highlighted in the introduction.

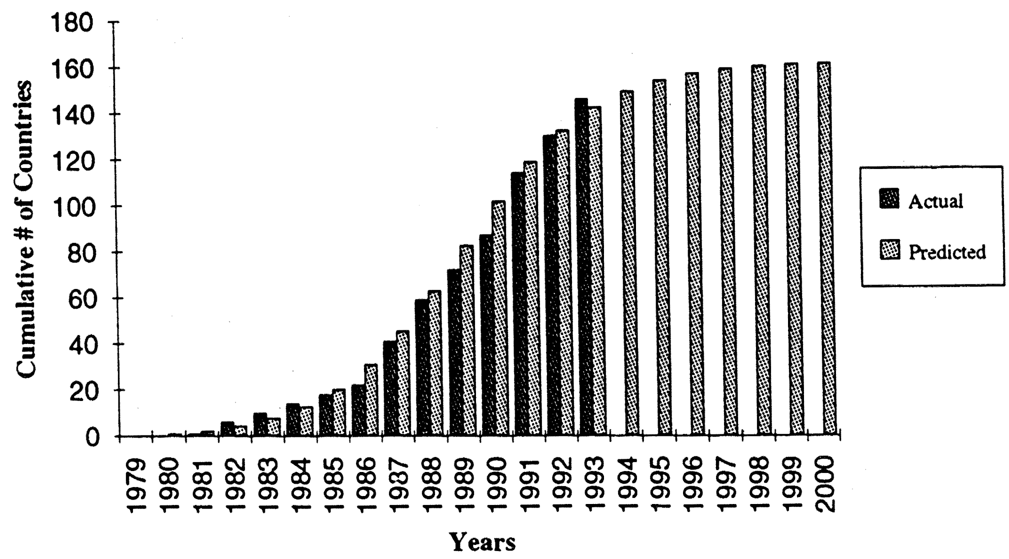
Our first hypothesis is related to a country's wealth and is derived directly from the diffusion literature. Rogers (1983)

Figure 1
VARIABILITY IN TRIAL TIME

First-Time Adoption



Cumulative Adoption



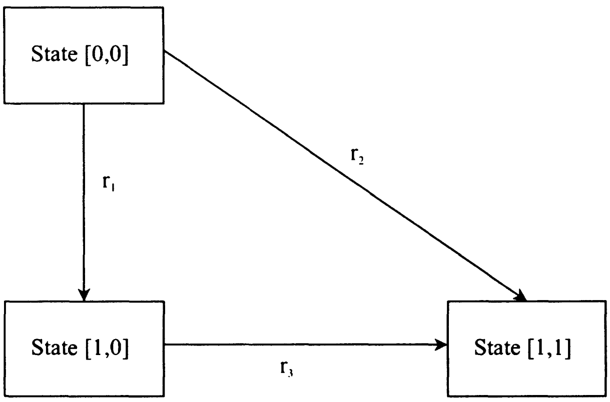
Notes: Predicted values are based on Easingwood, Mahajan, and Muller's (1983) aggregate diffusion model.

notes that innovators tend to have higher income (i.e., they can afford greater economic sacrifice to adopt the innovation). Translating this idea to an international context, several authors have argued that a society's adoption timing and subsequent diffusion rate are related to its standard of living and stage of economic development (Antonelli 1993; Gatignon and Robertson 1985; Helsen, Jedidi, and DeSarbo 1993). Indeed, wealth can enable a country to take higher risks (especially financial) to (partially or fully) adopt a technology. However, because the risks involved in trying the new technology on a limited scale are smaller than those involved in a full-substitution decision, we hypothesize a smaller effect on r_1 than on the other two transition rates. We therefore hypothesize the following:

H_{1a}: The three transition rates are positively affected by a country's wealth.
H_{1b}: The impact of a country's wealth is more pronounced on r_2 and r_3 than on r_1.

Our second hypothesis is related to the heterogeneity of a country's social system. Diffusion theory predicts that innovations diffuse more slowly in heterogeneous social systems (Gatignon and Robertson 1985). In the presence of a central decision-making unit, this effect still holds, as the decision-making unit may experience some difficulties in forcing all social system members to adopt the innovation. Therefore, industrywide consensus and coordination remain important in promoting the confirmation stage. We therefore expect that countries with heterogeneous social systems, where consensus and coordination are harder to obtain, will tend to reach full confirmation later, and we hypothesize a negative impact of social system heterogeneity on r_2 and r_3. In addition, although the implementation or trial stage depends more on the autonomous decision of the central decision maker (instead of the coordination of social system members), the social system might still be able to exert pressure on the central decision-making unit. Again, such pressure is

Figure 2
A MODEL OF GLOBAL DIFFUSION AS A REDUCED COUPLED SYSTEM



Notes: Digits in square brackets represent the completion (1) or noncompletion (0) of the implementation and confirmation stages, respectively. For example, [1,0] means that the implementation phase is complete but the confirmation phase is incomplete.

more likely to be effective in the presence of coordination and consensus between social system members. Thus, social system heterogeneity may negatively influence country adoption timing too, which would translate into a negative impact on r_1 and r_2. In their study on the diffusion of cellular telephone systems, Dekimpe, Parker, and Sarvary (2000) find support for the latter hypothesis: Social heterogeneity tends to delay the implementation stage. Given that the role of social system members is more pronounced in the confirmation stage, we hypothesize that social system heterogeneity has a stronger effect on r_2 and r_3 than on r_1. In summary, we formally test the following hypotheses:

H_{2a}: The three transition rates are negatively related to the heterogeneity of the country's social system.
H_{2b}: The effect of social system heterogeneity is larger on r_2 and r_3 than on r_1.

Our third hypothesis is related to the installed base of the old technology. Different factors are to be considered, such as the cost associated with the replacement of the old technology and network externalities. As the cost of replacing the old technology increases with the size of its installed base (Antonelli 1993), we hypothesize that full adoption (confirmation) of the new technology takes longer for countries with a large installed base of the old technology, which results in a negative impact on r_2 and r_3. Another factor, network externalities, may influence both stages of the adoption process. The economics literature on network externalities (e.g., Katz and Shapiro 1985, 1986, 1992; Shy 1996) argues that technologies with large installed bases tend to persist (become standards) even if better alternatives become available (a classic example being the QWERTY keyboard). The reason is that the incentives for a person to switch are smaller if the majority of other consumers are still using the old technology, and as a result the benefits of the new technology are significantly reduced. In other words, the (full) conversion of a larger installed base requires more coordination effort from the adopter population (or the central decision maker involved). As such, we expect this "technological inertia" to affect all three transition rates negatively.[5] However, because we expect the cost argument to be much more prevalent in the full-substitution decision, we hypothesize the effect of installed base to be stronger on r_2 and r_3 than on r_1.

H_{3a}: The three transition rates are negatively related to the size of the old technology's installed base.
H_{3b}: The installed base's effect is stronger on r_2 and r_3 than on r_1.

Our first three hypotheses consider exogenous factors specific to the country. Our next hypothesis considers a factor that is endogenous and relates to the worldwide diffusion process. It describes the effect of the cumulative international experience with the technology on a single country's diffusion process. Cumulative adoption by other countries may affect a single country in many ways. It represents a large network for the new technology, and to the extent that network externalities operate across consumers located in

[5]Although we provide a rationale based on network externalities for the negative effect of a large installed base on the speed of diffusion, our hypotheses are also in line with the findings of previous empirical research on the diffusion of new product substitutes (see, e.g., Norton and Bass 1987, 1992).

different countries (as is the case for telecommunications innovations, for example), the size of the international network helps the adoption process within a country (Arthur 1996).[6] It also provides increased incentives for a country that has not yet adopted the innovation to do so. Beyond network externalities, adoption by other countries also represents increased experience from which an individual country can benefit. For later adopters, the uncertainty associated with the new technology's relative advantage is significantly reduced. Furthermore, as the total number of worldwide adopters increases, better management methods and equipment may be available to allow for a smooth and less risky transition to the new technology. As such, we expect that later adopters can free ride on the experience of earlier adopters with the new technology. Finally, traditional word-of-mouth processes and peer pressure by other adopting members may also operate across countries (Mahajan and Muller 1994; Putsis et al. 1997), and this again promotes both stages of the diffusion process in a single country. Because we expect the cumulative international experience to increase over time, these effects also mean that countries adopting the innovation later will experience faster within-country diffusion. In their study on the diffusion of consumer durables in the Pacific Rim, Takada and Jain (1991) find that lagged adoption leads to an accelerated subsequent diffusion, a finding confirmed for other countries and product categories by Ganesh and Kumar (1996) and Ganesh, Kumar, and Subramaniam (1997). Formally,

H_{4a}: The three transition rates are positively related to the cumulative international experience with the technology.

H_{4b}: The trial time of a country has a positive effect on r_3.

Our next hypothesis is related to the effect of a country's own experience with the innovation, for which the total number of adopters within the country is a natural measure. As indicated before, this hypothesis only applies to countries that have reached State [1,0] and therefore only affects rate r_3.

H_5: Transition rate r_3 is positively affected by the country's own experience with the technology.

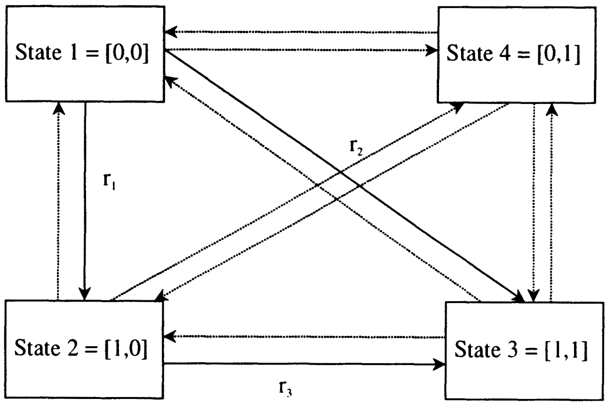
EMPIRICAL MODEL DEVELOPMENT

This section develops a formal statistical model to test the hypotheses outlined previously. We model time until trial and time until confirmation through two interdependent failure-time processes, each of which has two states, 0 (reflecting, respectively, that no trial has been initiated or that no confirmation has been reached yet) and 1 (when trial has been initiated for the trial process or when full substitution has been reached for the confirmation process).

The joint evolution of both processes is modeled through the coupled approach described by Petersen (1995) and Tuma and Hannan (1984, Chapter 4). Conceptually, a bivariate system of dichotomous states results in four possible coupled states: [0,0] reflects the state countries are in when

Figure 3

THE GENERAL COUPLED SYSTEM WITH FOUR STATES



Note: Digits in square brackets represent the completion (1) or noncompletion (0) of the implementation and confirmation stages, respectively. For example, [1,0] means that the implementation phase is complete but the confirmation phase is incomplete.

they have not yet initiated trial or reached full substitution, [1,0] reflects trial without confirmation, [0,1] reflects full confirmation without trial,[7] and [1,1] reflects the attainment of both trial and confirmation. The dynamics within the system are fully described by the instantaneous transition or hazard rates between the different states, as is illustrated by the different arrows in Figure 3.

As shown in Figure 3, the number of rates in the general case equals 12 (i.e., J (J – 1), where J is the number of coupled states); however, the estimation of this number may prove problematic in a global diffusion context, as the sample size for each individual process will be determined by the number of countries (< 200) on which data are available. Fortunately, not all states can be obtained from certain states, which results in the restriction of multiple transition rates to zero (Blossfeld and Hamerle 1989). These restricted transition rates are represented by dashed arrows in Figure 3. For example, confirmation cannot be reached before trial, which results in a restriction on the transition rate from State 1 to State 4. Moreover, we never observe a discontinuance of the diffusion process (i.e., the rejection of the innovation by a country after it has tried the technology), which implies that all rates entering State 1 can be set to zero (Petersen 1995). Because of these intricacies of the considered global diffusion process, Figure 3 reduces to Figure 2, in which only the three instantaneous transition rates discussed previously remain to be estimated. These rates are represented by full arrows in Figure 3 and denoted (as previously) by r_1, r_2, and r_3. One of these transition rates, r_2, models explicitly the possibility that some countries replace their entire installed base of the old technology at once and therefore obtain a 100% penetration in their first adoption period.

Upon the new technology's arrival (i.e., at time t_0), all countries occupy State 1, that is, the [0,0] state. Depend-

[6]In the context of digital telecommunication networks, the new technology allows for higher quality communications and the introduction of new services. In telephony, for example, a digital network substantially increases the quality of many Internet services. As the pool of countries with high-quality networks grows, the remaining countries (or regions in a country) benefit more from joining the network.

[7]This state can never materialize. We elaborate subsequently on the simplifications arising from conceptually impossible states and/or transitions.

ing on the observed transitions during the observation window $[t_0, t_{end}]$, four scenarios can be distinguished, which will result in different contributions to the likelihood function.

Scenario A

No trial or full confirmation is obtained, which implies that the country is still in State [0,0] at the end of the observation period. As shown in Vilcassim and Jain (1991) and Petersen (1995), this scenario results in the following contribution to the likelihood function:

$$(1) \quad L_A = \left[\exp\left\{-\int_{t_0}^{t_{end}} r_1(\tau)d\tau\right\}\right]\left[\exp\left\{-\int_{t_0}^{t_{end}} r_2(\tau)d\tau\right\}\right] = \exp\left\{-\int_{t_0}^{t_{end}} [r_1(\tau)+r_2(\tau)]d\tau\right\}.$$

The first term in this expression indicates that no transition has occurred from State [0,0] to State [1,0], whereas the second term precludes an observed transition from State [0,0] to State [1,1]. $r_1 + r_2$ gives the overall exit rate from State [0,0], that is, the overall trial rate, where r_1 and r_2 are defined as type-specific hazard (exit) rates (Kalbfleish and Prentice 1980):

$$(2) \quad r_j = \lim_{\Delta t \to 0} \frac{P(t \le T_{trial} < t + \Delta t, J = j \mid T_{trial} \ge t)}{\Delta t}, \quad j = 1, 2,$$

which are defined conditional on neither event's (exit to [1,0] or exit to [1,1]) happening before t.

Scenario B

At time t^* ($< t_{end}$), a transition to State [1,1] is observed, which implies that a country has reached an instantaneous full confirmation during the observation period. Under this scenario, the following contribution to the likelihood function is obtained:

$$(3) \quad L_B = \left\{r_2(t^*)\exp\left[-\int_{t_0}^{t^*} r_2(\tau)d\tau\right]\right\}\left\{\exp\left[-\int_{t_0}^{t^*} r_1(\tau)d\tau\right]\right\}.$$

The first term indicates that at time t^* a transition is observed from State [0,0] to State [1,1] (see Kalbfleish and Prentice 1980; Petersen 1995; Vilcassim and Jain 1991). The second term, by contrast, ensures that in this same time span no transition was observed from State [0,0] to State [1,0].

Scenario C

At time t^*, trial is initiated, but during the observation period, no full substitution is obtained. Using a similar logic, it is easy to show that the corresponding likelihood contribution can be written as

$$(4) \quad L_C = \left\{r_1(t^*)\exp\left[-\int_{t_0}^{t^*} r_1(\tau)d\tau\right]\right\}\left\{\exp\left[-\int_{t_0}^{t^*} r_2(\tau)d\tau\right]\right\}\left\{\exp\left[-\int_{t^*}^{t_{end}} r_3(\tau)d\tau\right]\right\}.$$

The first two terms in Equation 4 are conceptually similar to those in Equation 3. The final term, however, ensures that in the interval $[t^*, t_{end}]$ no transition from State [1,0] to State [1,1] is observed.

Scenario D

Finally, the case can be considered in which the trial phase is started at time t^*, whereas the confirmation stage is obtained only some time later (i.e., at $t^{**} < t_{end}$). The corresponding likelihood contribution becomes

$$(5) \quad L_D = \left\{r_1(t^*)\exp\left[-\int_{t_0}^{t^*} r_1(\tau)d\tau\right]\right\}\left\{\exp\left[-\int_{t_0}^{t^*} r_2(\tau)d\tau\right]\right\}\left\{r_3(t^{**})\exp\left[-\int_{t^*}^{t^{**}} r_3(\tau)d\tau\right]\right\}.$$

Compared with Equation 4, only the last term differs and now indicates the transition from State [1,0] to State [1,1] at time t^{**}. It should be noted that $r_3(.)$ is defined (i.e., is nonzero) from the arrival in State [1,0] onward, which implies that the duration dependence in $r_3(.)$ captures the time since a given country's trial, as opposed to the time since the innovation became available (Tuma and Hannan 1984).

The different scenarios can be combined easily into an overall log-likelihood expression for all N countries by defining four mutually exclusive indicator variables $d_{J,i}$:

$$(6) \quad LL = \sum_{i=1}^{N} d_{A,i}\ln(L_{A,i}) + d_{B,i}\ln(L_{B,i}) + d_{C,i}\ln(L_{C,i}) + d_{D,i}\ln(L_{D,i}),$$

where $d_{J,i} = 1$ if country i falls under scenario J (J = A,B,C,D), and zero otherwise.

To test the relevant research hypotheses, a formal relation still needs to be specified between the transition rates and the covariates of interest:

$$(7a) \quad r_{i,1}(t) = r_{0,1}(t)\exp[\beta_1 X_{i,1}(t)],$$

$$(7b) \quad r_{i,2}(t) = r_{0,2}(t)\exp[\beta_2 X_{i,2}(t)],$$

and

$$(7c) \quad r_{i,3}(t) = r_{0,3}(t)\exp[\beta_3 X_{i,3}(t)],$$

where the $X_{i,j}(t)$ reflects the values (for country i) of the explanatory variables that influence transition rate j (j = 1, ..., 3),

β_j is the parameter vector to be estimated, and $r_{0,j}(t)$ reflects the baseline hazards in the respective transition rates. Two specifications will be implemented, the exponential baseline model as used by Hannan and McDowell (1984) and the Weibull specification used by Chandrashekaran and Sinha (1995). Finally, to describe the time path of the time-varying covariates, we adopt the common simplifying assumption that they remain constant within a time interval (in our case, a year) but are allowed to change across intervals. Under this assumption, the expressions in Equations 1–5 can be substantially simplified (for a similar assumption and corresponding derivations, see Dekimpe et al. 1998; Gupta 1991; Vanhuele et al. 1995). For example, in case of an exponential baseline, Equation 1 becomes

$$(8) \qquad L_A = \{\exp[-r_{0,1}B_1(t_{end})]\}\{\exp[-r_{0,2}B_2(t_{end})]\},$$

where

$$(9a) \qquad B_1(t) = \sum_{j=1}^{t} \exp[\beta_1 X_1(j)],$$

$$(9b) \qquad B_2(t) = \sum_{j=1}^{t} \exp[\beta_2 X_2(j)],$$

and $r_{0,1}(r_{0,2})$ gives the (constant) baseline hazard. In case of a Weibull baseline, the exp{.} terms in Equations 9a and 9b are augmented with $[\gamma_1 \ln(j)]$.[8] Similar expressions can be derived for Equations 3–5 and are available from the authors on request.

Following Lillard (1993, p. 189) and Petersen (1995, p. 321), the interdependence between two hazard processes can be specified as a rate dependence (in which the hazard rate of one process depends on the rate of the other)[9] or as a state dependence (in which the hazard of one process depends on the state of the other process). The coupled framework described previously is situated within the second research tradition,[10] in that the rate with which full substitution is obtained (the confirmation process) depends on the state of the implementation process. As such, three sets of parameters (r_1, r_2, and r_3) are estimated to describe the two stages of the adoption process. None of these three transition rates can be individually identified with either of the two stages (implementation and confirmation); rather, it is the combination of all three rates that provides a full picture of the two interlinked stages. Apart from this state dependence, the model also allows for a so-called (lagged) duration dependence (see Flinn and Heckman 1982), as the time of arrival into State [1,0] will be entered as a covariate to explain variations in r_3. In other words, the length of time the implementation process stays in State [0,0] may determine the exit rate of the confirmation process out of State [1,0].

Parameter estimates are obtained through full-information maximum likelihood estimation, that is, by optimizing the joint likelihood function in Equation 6. However, this expression is separable, and by appropriately redefining the censoring dummies, the three transition rates can be estimated separately through standard hazard-rate procedures (for a more detailed discussion, see Petersen 1995): r_1 when treating the observations in Scenarios C and D as completed and those in Scenarios A and B as censored, r_2 when treating the observations in Scenario B as completed and all others (i.e., A, C, and D) as censored, and r_3 by considering only the observations in Scenarios C and D and treating the former as censored and the latter as completed. Therefore, although the proposed coupled approach explicitly takes the interdependence between the implementation and confirmation stages into account, standard estimation procedures can still be applied. Both estimation procedures are implemented (the joint estimation of Equation 6 and the three separate estimations) as a validity check against local optima. In addition, different starting values are used in each instance to assess whether convergence to the same estimates is obtained.

It should be emphasized that this separability property does not imply that the implementation and confirmation stages are modeled as two independent processes. Rather, it is a nice feature of state dependency models that such separation is possible, provided that the dependency is captured through observable variables or states (for detailed discussions, see Lillard 1993, p. 200; Montgomery 1992, p. 102; Petersen 1995, section 6).[11] In case of correlated unobserved heterogeneity across r_1, r_2, and r_3, such separate estimation is no longer possible, however. Corrections for (possibly correlated) unobserved heterogeneity are left as an important area for further research.[12]

EMPIRICAL STUDY

We now turn to an empirical application of the proposed modeling approach and test H_1–H_5 on data collected on the trial and confirmation stages of digital telephony across 162 countries.

Duration Data

Data on the relevant durations were collected from the International Telecommunications Union, a United Nations agency. The starting point for the time until trial is 1979 for every country, and for those 12 countries that had not yet started the adoption process the common censoring date was 1993. For the time until full substitution after partial trial, both the starting date and the potential censoring date varied across countries. The former variability is caused by differences in the trial time (as discussed previously), whereas the variability in the censoring dates is due to the specific characteristics of the data set. In Egypt, for example, 40% of the telephone network was serviced through digital switches in 1992, but no percentage was available for 1993. As such, the end of the observation period for Egypt was taken to be 1992. For Iceland, in contrast, the percentage substituted in

[8]To ensure the nonnegativity of $r_{0,j}$, it is operationalized as $\exp(\gamma_{0,j})$.

[9]See, for example, Lillard (1993) or Lillard and Waite (1993).

[10]See, for example, Courgeau and Lelièvre (1992), Montgomery (1992), Petersen (1995), or Tuma and Hannan (1984, Chapters 4 and 16) for other applications.

[11]Note that this separability still holds in the case of uncorrelated unobserved heterogeneity terms.

[12]We did not implement these corrections in the current application for two reasons: (1) the choice between specifications with and without correction for unobserved heterogeneity involves a trade-off between completeness and simplicity. Given the limited number of (completed) observations in our sample, we did not want to overparameterize the model. (2) Previous experiences with taking unobserved heterogeneity into account (even in single-equation models) have been mixed, especially in smaller samples (see, e.g., Hoem 1989; Trussell and Richards 1985).

1993 (66%) was available, so 1993 was taken to be the censoring point for that country. Therefore, we take a conservative approach: For those countries for which a 100% substitution rate is not reported, we censor at the last year for which reliable data are available. In doing so, we take all useful information into account, because the survival function for those countries reveals that in the time span we observe (which may vary from country to country) no full substitution was reached. The relative frequency of the different scenarios described in the modeling section is given in Table 2, where we also give the relative frequencies of censored and completed observations when estimating the three transition rates separately.

Operationalization of the Variables

Following Antonelli (1993) and Helsen, Jedidi, and DeSarbo (1993), among others, we use gross national product (GNP) per capita (expressed in tens of thousands of dollars) to measure a country's wealth, and we use the number of ethnic groups in the country as a measure of its social system's heterogeneity (for a similar operationalization, see Dekimpe, Parker, and Sarvary 1998, 2000). The size of the installed base of the old technology (in millions of lines) is measured differently in the respective transition rates. For r_1 and r_2, the size of the telephone network at the end of the preceding period is used. For example, the transition rate in Period 1 (i.e., adoption in 1979) is modeled as a function of the number of telephone lines in 1978, in Period 2 as a function of the number of lines in 1979, and so forth. For the confirmation stage (r_3), however, the number of lines not yet serviced through digital switches is computed in every period. In doing so, we account for the remaining installed base of the old network technology gradually becoming smaller as the confirmation stage progresses. The installed base varied greatly across countries and showed a highly skewed distribution. To reduce the skew in the data and to avoid having a small number of extreme observations driving our empirical findings (Hamilton 1992), we took the natural log of the installed base as an explanatory variable (for a similar practice, see Dekimpe et al. 1997).[13] Finally, the time of trial (the extra covariate in r_3 to test H_{4b}) is measured relative to 1979, the year the technology became available.

Data on these explanatory variables were collected from Euromonitor Ltd. and the *World Factbook* (Central Intelligence Agency 1993). One of them, the size of the existing telephone network, is time varying. All other covariates are treated as time-invariant; that is, we assume that they did not vary in a systematic fashion over the considered time span. Relevant summary statistics are presented in Table 3, and traditional collinearity tests revealed no serious problems between the time-invariant covariates. Ideally, a multi-item scale should be developed for each of the constructs discussed in the theory section. However, as applied interna-

[13]Similar substantive findings (sign and significance) were obtained when we used other skewness-reducing transformations (e.g., the square root) or when working with the untransformed observations.

Table 2
NUMBER OF OBSERVATIONS IN DIFFERENT SCENARIOS

A: Confirmation = 100% Substitution				
Joint Estimation		*Separate Estimation of the Different Transition Rates*		
		r_1	r_2	r_3
Scenario A	12	Completed: 133	Completed: 17	Completed: 10
Scenario B	17	Censored: 29	Censored: 145	Censored: 123
Scenario C	123			
Scenario D	10			
Total	162	162	162	133

B: Confirmation = 90% Substitution				
Joint Estimation		*Separate Estimation of the Different Transition Rates*		
		r_1	r_2	r_3
Scenario A	12	Completed: 127	Completed: 23	Completed: 18
Scenario B	23	Censored: 35	Censored: 139	Censored: 109
Scenario C	109			
Scenario D	18			
Total	162	162	162	127

Table 3
SUMMARY STATISTICS

Covariate (N = 162)	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
GNP per capita (tens of thousands of dollars)	.438	.655	.007	3.030
Number of ethnic groups	5.1	2.6	1	15
Number of analogue lines in 1978 (millions)[a]	1.807	8.726	.0003	99.449
Year of implementation[b]				
Scenarios B, C, D (N = 150)	1988.2	3.026	1980	1993
Scenarios C, D (N = 133)	1987.9	3.049	1980	1993

[a]Summary statistics are given for the year preceding the year of introduction. In the hazard specification, the covariate is included as time varying.
[b]Summary statistics are based on countries that have completed the implementation stage.

tional researchers are well aware, it is difficult to find globally representative proxies for more than 160 countries.

There are several options for operationalizing the time-varying construct "cumulative international experience." We implement three operationalizations. First, as Helsen and Schmittlein (1993) argue, we can operationalize it with the passage of time. In this context, the positive effect of experience on the process is reflected in an increasing base transition rate. For r_3, the baseline hazard captures the additional experience since arrival into State [1,0]. However, the extent of international experience upon arrival in State [1,0] will be larger for laggards than for early adopters, and therefore in H_{4b} we hypothesized an additional positive impact on r_3 of the year of trial, which implies that countries that try the innovation later will reach full confirmation sooner. A second operationalization of the international experience effect uses the total number of countries that have already tried the technological innovation. This operationalization is in line with the interfirm diffusion literature (see, e.g., Ganesh and Kumar 1996) and measures each country's adoption as a dichotomous variable (i.e., has or has not adopted; but this variable does not yet take into account the extent of the adoption). Third, the total number of innovations (e.g., digital switches) adopted in the world could also be used. This approach is consistent with the learning measures proposed by Mahajan and Muller (1994) and Putsis et al. (1997), among others. In this case, the influence of the different countries is not uniform but weighted by their own accumulated experience.[14]

Analysis

Parameter estimates for the respective transition rates are given in Table 4, where we operationalize the international experience effect through the (Weibull) baseline specification (see Helsen and Schmittlein 1993). The slope coefficient of the Weibull baseline (γ_1) is positive and significant in each of the three transition rates, thereby in support of H_{4a}. The upward pattern in r_3 supports the notion that the experience (own + others') gained after arriving in State [1,0] positively affects the subsequent substitution rate. However, in H_{4b}, we also postulated that the time of entry in State [1,0] affects this transition rate, as later entrants benefit from more accumulated prior experience. This hypothesis was also supported by the data, as is evidenced by the positive and significant coefficient of the time-of-trial variable, thereby confirming previous research findings by Takada and Jain (1991) and Ganesh and Kumar (1996).

We now turn to the other factors, which stand to characterize cross-sectionally the three transition rates. H_{1a} states that all three transition rates should be faster for wealthier countries. This hypothesis is supported, which implies that richer countries complete the confirmation as well as the implementation stage faster. A likelihood ratio test on the equality of its impact on the three transition rates could not be rejected, however (LR = $1.914 < \chi^2_{.90,\,2df}$); that is, H_{1b} is not supported.

H_{2a} argues that the ethnic heterogeneity of a country has a negative impact on all three transition rates. This hypothesis was only partially supported. Although ethnic heterogeneity had a negative impact on transition rates r_2 and r_3, which confirms the conjecture by Gatignon and Robertson (1985), it did not affect r_1 (thereby supporting the differential effects hypothesis, H_{2b}). This verifies our conjecture that social consensus is not as crucial for the trial phase of the diffusion process as for the confirmation phase.

Similar to ethnic heterogeneity, the impact of the old technology's installed base had a strong negative impact on r_2 and r_3 (partially supporting H_{3a}) but no impact on r_1 (supporting H_{3b}). Consistent with Antonelli's (1993) conjecture, the larger the installed base, the higher the cost associated with the full replacement of the old technology and, as a result, the longer the confirmation stage. The result also illustrates the phenomenon of technological inertia underlined in the literature: Even if the innovation is available in the social system, social system members are reluctant to switch to the new technology. The partial introduction of the new technology does not depend on the size of the installed base.[15]

[14]The three measures (which are all time varying) are correlated to some extent, so we cannot include them simultaneously in the model. Therefore, when using the second (number of countries adopted) and third (number of lines already replaced) operationalizations, we use the exponential model as baseline specification.

[15]This again might suggest that the central decision makers act somewhat independently from the social system (which nicely illustrates the conceptual difference between the two stages of the diffusion process). In the case of technological innovations, inertia could prevent the introduction of innovations. Through regulation, a central decision maker can promote the introduction of the new technology in spite of the social system members' reluctance.

Table 4
PARAMETER ESTIMATES: WEIBULL BASELINE

	Transition Rate 1: State [0,0] → [1,0]	*Transition Rate 2: State [0,0] → [1,1]*	*Transition Rate 3: State [1,0] → [1,1]*
γ_0	–6.93[a]	–19.24[a]	–15.99[a]
γ_1	2.33[b]	6.19[b]	3.28[b]
GNP per capita	.26[b]	1.07[c]	.83[c]
Ethnic heterogeneity	–.00	–.29[b]	–.47[b]
Installed base of old technology	.19	–.47[b]	–.64[b]
Time of trial	—	—	.79[b]
Log-likelihood (separate estimation)	–383.98	–61.41	–35.06

[a]Significant at $p < .05$, two-sided test.
[b]significant at $p < .05$, one-sided test.
[c]Significant at $p < .1$, one-sided tests.
Notes: Log-likelihood (joint estimation) = –480.45 [consistent Akaike information criterion = 1042.40; Bayesian information criterion = 1042.30].

Robustness Tests

Sensitivity to the operationalization of international experience. In Table 4, we operationalized the international experience effect through an increasing baseline hazard in the respective transition rates. As a validation check, we implemented the two other operationalizations discussed previously: the number of countries that have adopted the new technology and the number of lines that have been switched to the new technology.[16] As illustrated in Table 5, in every instance support for H_{4a} was still found, as was reflected in the significant, positive coefficients of the experience effect in each of the transition rates. Moreover, the other substantive insights were again comparable to the ones reported in Table 4 (detailed results are available from the authors on request).[17] When we incorporated as separate covariates into r_3 the cumulative number of foreign lines already switched and the cumulative number of own lines already substituted, we found the latter coefficient to be positive and significant, which thereby supports H_5.

Can decreasing prices explain the increasing baseline hazard? An alternative hypothesis for the increasing baseline hazard in Table 4 could be a decreasing price trend for the digital switches, as is often the case for technological innovations. We did not have price data over time for the different countries in our data set but collected monthly (inflation-adjusted) U.S. price data for the period from January 1986 to December 1993. A deterministic trend regression on these data did not reveal a negative price evolution, however [$\beta_{trend} = +.03$; $t_{trend} = 3.26$].

Relaxation of the full-substitution requirement. Thus far, we defined confirmation as a 100% substitution rate, which clearly is a fairly stringent criterion. The time needed to reach 90% substitution could also be considered, which corresponds to the takeover time in Fisher and Pry's (1971) specification. This less stringent definition of confirmation caused more observations to fall under Scenarios B and D, as described in Panel B of Table 2, and therefore more completed observations in the estimation of the respective transition rates. Overall, the same substantive conclusions were obtained (see Table 6): (1) richer countries are more innovative, (2) heterogeneity in the social system delays confirmation, (3) the size of the installed base affects the speed of obtaining full confirmation but not the time of trial, (4) cumulative international experience matters for all three transition rates, and (5) later adopters reach full substitution earlier. The only difference observed was in rate r_3, for which the GNP-per-capita variable, though still positive, was no longer significant.

SUMMARY AND EXTENSIONS

Diffusion processes result in the acceptance or penetration of a new idea, behavior, or physical innovation over time by a given social system. In a global context, when the social system is the community of nations, we theorize that diffusion across countries takes place in two distinct, though related, phases: the implementation or trial stage and the confirmation stage. In this article, we propose a coupled-hazard approach to model this process and test research hypotheses generated from the extant literature. Our objective was to understand the diffusion dynamics of a special product category, technological innovations, which requires that diffusion theory and the resulting models be adapted to take

[16]As indicated previously, to avoid multicollinearity problems among the different time-varying covariates, we incorporated these other measures of international experience in a model with an exponential baseline hazard. Similarly, both new operationalizations were implemented one at a time.

[17]The only difference was that GNP per capita was no longer significant in r_1 (both new operationalizations) and r_2 (when working with the number of lines switched), even though the signs remained positive.

Table 5

OTHER OPERATIONALIZATIONS OF THE EXPERIENCE EFFECT

	Transition Rate 1: State [0,0] → [1,0]	*Transition Rate 2: State [0,0] → [1,1]*	*Transition Rate 3: State [1,0] → [1,1]*
Cumulative number of countries that tried at t – 1	.022	.038	.033
Cumulative number of lines switched at t – 1 to the new technology (millions)	.009	.016	.012

Notes: All figures are significant at $p < .05$, one-sided test. Log-likelihood = –496.43 (operationalization 1), –511.20 (operationalization 2).

Table 6

PARAMETER ESTIMATES: 90% SUBSTITUTION

	Transition Rate 1	*Transition Rate 2*	*Transition Rate 3*
γ_0	–6.79[a]	–17.71[a]	–11.93[a]
γ_1, Weibull	2.25[b]	5.82[b]	2.80[b]
GNP per capita	.23[c]	1.00[b]	.35
Ethnic heterogeneity	.00	–.25[b]	–.11
Installed base of old technology	.21	–.36[b]	–.34[b]
Time of trial	—	—	.49[b]

[a]Significant at $p < .05$, two-sided test.
[b]Significant at $p < .05$, one-sided test.
[c]Significant at $p < .1$, one-sided test.
Notes: Log-likelihood (joint estimation): Weibull = –522.20.

into account the effects of network externalities, such as the potential for a non-S-shaped diffusion pattern in some countries (e.g., due to immediate full substitution) and the considerable impact of the old technology's installed base.

Our empirical results provide interesting theoretical insights and have important managerial implications. We find strong international contagion effects: The more countries that have adopted or the longer the international experience with an innovation, the higher the chances that other countries will also implement the innovation. For the empirical case studied (digital telephony), we also find that innovative countries are wealthier (consistent with Gatignon and Robertson's [1985] observation at the individual level for consumer goods). We also find that countries with homogeneous social systems reach full confirmation faster (as hypothesized by Gatignon and Robertson 1985) and that laggard countries have faster within-country diffusion rates (consistent with Takada and Jain 1991). For the rates describing transitions to full substitution (i.e., r_2 and r_3), our data provide strong evidence for a negative installed-base effect.

Our empirical findings are based on the observed diffusion process of one high-technology industrial product. Still, our modeling approach is general, and with minor modifications it is applicable to the global diffusion of all product innovations. For example, the globalization process 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 cases, as in this particular application, diffusion is of a "decentralized" nature if the manufacturers themselves do not determine when sales will begin in a specific country, but instead individual governments determine (even though the firms may try to influence that decision) the point from which the innovation is either implemented or fully confirmed. This decentralized nature of the diffusion process is reflected in our choice of covariates, in that they describe characteristics of the countries rather than those of technology providers such as Alcatel, AT&T, Ericsson, or Siemens.[18] Further research that considers centralized diffusion processes, using the modeling approach presented, may find support for some of the hypotheses presented and may therefore lead to greater insights into globalization patterns.

On a more technical level, several extensions to the proposed coupled approach could be envisioned. First, we modeled the interdependence between the implementation and confirmation processes by means of a state dependency (Petersen 1995); that is, the relevant rate of change in the confirmation process (r_2 versus r_3) was a function of the state of the implementation process (0 or 1). In addition, we modeled the rate of full substitution after partial trial (i.e., r_3) as an explicit function of the time of trial, which reflects what Flinn and Heckman (1982) call a lagged-duration dependence. As indicated previously, we could also model the interdependence between both processes as rate dependencies, that is, model the confirmation rate as a function of the implementation rate (and/or vice versa). This would result in a simultaneous or recursive system of hazard rates, as was recently explored by Lillard (1993). A third way of modeling the interdependence between the relevant durations would be to combine the respective univariate distributions into a correlated multivariate distribution, as Chintagunta and Haldar (1998) illustrate for the bivariate case. More research on the relative advantages of the different approaches would be useful but is beyond the scope of this research.

Second, our framework allowed for interdependence only through the observed covariates. No correction for unobserved heterogeneity, possibly correlated across the three transition rates, was made. A useful extension may be to add such a correction to the proposed model.

Third, we did not allow for a reversal of the diffusion process. Although this phenomenon did not occur for the technology at hand, it might well occur for other innovations. The coupled approach given in Figure 3 could still be used in those instances (for a more elaborate discussion, see, e.g., Petersen 1995; Tuma and Hannan 1984), even though Figure 3 would no longer reduce to the simpler Figure 2 and more complex likelihood expressions would need to be optimized.

[18]It should be noted that decentralized processes are likely to exist for a wide variety of product categories, such as medical products, telecommunications services, energy supply systems, electronic products that must meet local type approval, cosmetics, or any other packaged consumer goods that require government approval or face nontariff barriers.

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