GLOBAL DIFFUSION OF NETWORK TECHNOLOGIES: A DOUBLE-HAZARD APPROACH

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Revised: April 1997

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Abstract

The paper proposes a "double-hazard" approach to explain the global diffusion of network innovations. Network products are those which interconnect large yet dispersed populations. New network technologies may complement or substitute existing ones which themselves have already undergone, or are currently undergoing, international adoption. We first model the timing when a country tries or "pilot tests" the network technology, called "the implementation stage" by Rogers (1983). We then model the timing of when the innovation is implemented on a national or ubiquitous basis within the country (referred to by Rogers as the confirmation stage), and assess the interrelationship between both processes. In order to test relevant research hypotheses concerning the international diffusion process of these types of products, we apply the proposed approach to the diffusion of digital telecommunications networks across 160 countries.

INTRODUCTION

With the increasing globalization of markets, managerial interest in understanding adoption processes across countries has lead to calls for more academic research on international diffusion (see e.g. Douglas and Craig 1992). While a number of 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 paper is the first to consider the *global* diffusion of a particular form of innovation: enhancements to network technologies. Network products are those which interconnect large geographically dispersed populations. New network technologies which are launched to better serve the society's members, often complement or modify existing ones which themselves have already undergone or are still undergoing a diffusion process. Examples include the substitution of analogue telephone switches by digital ones and the evolution of mobile telecommunication technologies over time. As illustrated in Norton and Bass (1987, 1992), both diffusion processes are interlinked, raising questions on whether an old network technology will be fully substituted by a newer generation, and to what extent the size of already installed networks of the old technology affects the speed of diffusion of the newer generation. While previous research has dealt with these issues in a *domestic* context using *aggregate models*, we address them using *individual-level* adoption models in an *international* setting. Three aspects of this diffusion process (its global nature, the diffusion of network products as opposed to "conventional" consumer durables, and the substitution issue) generate interesting theoretical and modeling challenges.

First, we argue that global adoption is comprised of two stages. Our framework considers the two stages as separate but related measures of innovativeness across countries:

[1] Gatignon, Eliashberg and Robertson (1989) and Mahajan and Muller (1994), for example, compare the Bass diffusion parameters for a number of household appliances across a set of European countries. Takada and Jain (1991) compare these diffusion parameters for four Pacific Rim countries, and Helsen et al. (1993) assess similarities in the diffusion of three consumer durables across 12 industrialized countries. In a recent paper involving 10 European countries and four durable products, Putsis et al. (1997) provide an innovativė model of cross-country diffusion describing the "mixing behavior" of heterogeneous populations.

- the time between when an innovation first becomes available and the time it first appears in a country, i.e. the *implementation* stage (as defined by Rogers 1983), and
- the time between the initial trial within a country and its full adoption or substitution, which captures the length of the *confirmation* stage (as defined by Rogers 1983).

From a managerial perspective, both aspects may influence production and/or marketing planning decisions. For example, the likely adoption (trial) date for some countries may lie well beyond the firm's typical planning horizon. Similarly, once the initial adoption decision has been made, managers become interested in the subsequent speed of diffusion of the new technology within that country, i.e. how long it will take the country to fully replace the old technology.

Second, while all global products diffuse in the manner theorized above, network technologies, in particular, have unique characteristics vis-à-vis other industrial or consumer goods. We define network products as those which interconnect large geographically dispersed populations. As such, network products generally impose a standard upon users and can only be of value if a sufficiently large proportion of the target population simultaneously adopts (or is forced to use) the network (Economides 1996). This characteristic, called "network externality" (Katz and Shapiro, 1985) leads to diffusion patterns unlike most other consumer or industrial innovations'.[2] Consider, for example, Table 1 which illustrates four network diffusion scenarios. For Country A, in Table 1, the implementation and confirmation stages can not be distinguished in time. In the specific instance of digital-communication switches, countries like Gabon, Gambia, and Jamaica implemented digital technology on an ubiquitous basis within their first year of adoption. Clearly, this type of adoption behavior (100% penetration in the first year) runs counter to the notion that adoption patterns within a social system, follow an S-shaped penetration curve in every single country. In these cases within country contagion effects (e.g. interpersonal influence or learning effects) across the product users (e.g. network users) are simply absent. While some countries reach full penetration at the moment of adoption, others exhibit a diffusion pattern that resembles the familiar S-shape adoption pattern (see Country B in Table 1). In these countries, network technologies are slowly adopted for either temporal or geographical reasons elaborated on below.

[2] Network externalities may be present even if the new network technology is compatible with the old one. The reason is that the benefits of the new technology (e.g. higher communication quality) materialize only if both ends of the communication chain use the superior technology.

Such was the case for some countries (e.g. France, Finland, Hong Kong and the Dominican Republic) which maintained a mixture of digital and analogue telecommunications networks for several years after their initial trial of the newer digital technology. In these cases, S-shaped diffusion may not only be a function of interpersonal influence, but also of network externalities (i.e. a larger population of adopters increases the benefit of joining the network). 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 illustrated by Countries C and D in Table 1. Using again the digitization example, Gabon and Gambia went to immediate full substitution in 1987, while the Maldives did so in 1991. As for the gradual substitution, France started the process in 1981, while Israel initiated the process only eight years later.

Third, since new network technologies often complement or modify existing ones which have undergone or are still undergoing a diffusion process, the product substitution literature raises two additional issues. Specifically, (1) whether the new technology will fully replace the old one, and, (2) how will the size of the old technology's installed base affect the speed of substitution? "Full replacement" is a standard assumption of product substitution models but previous research has failed to provide empirical tests for this assumption. In our context this issue breaks into separate questions for the implementation and confirmation stages, both having important managerial implications. In the implementation stage, we are interested in testing if all countries will ultimately adopt the new technology; in the confirmation stage we are interested in knowing if the new network technology will fully replace the old one in every country. Our model allows us to provide rigorous empirical tests for both of these hypotheses. The second issue raised by the literature is related to the size of the installed base. Our empirical model also allows us to measure the impact of the old technology's installed base on both stages of the international diffusion process.

In what follows, we first present a theoretical framework and related research hypotheses. Extending diffusion theory to the international context, we consider four general factors of theoretical interest for global diffusion: (1) economic, (2) political, (3) social/demographic, and (4) network. Next, we propose a "double hazard" modeling approach appropriately adapted to network technologies undergoing global diffusion and flexible enough to test various research hypotheses. Unlike traditional aggregate diffusion models (e.g. Bass 1969), the proposed approach is applicable to network technologies by allowing full adoption in the first year after trial for some countries, and gradual adoption in others. It also allows to test if all countries will fully adopt the new technology. Following the model discussion, we then turn to empirical tests using data collected from the telecommunications industry, for which we explore the timing of digital network implementation (first digital-system installation) and full substitution (all analogue systems being replaced by digital systems within a given country) across the global marketplace; over 160 countries are considered which are located across all continents: 51 in Africa, 38 in Asia, 37 in the Americas, 27 in Europe and 9 in Oceania.[3] Throughout the model presentation we will refer to the digitization of telecommunications services as a working illustration. For this network technology, we identify characteristics that allow researchers/managers to distinguish between countries along Rogers' (1983) "innovator-laggard" continuum and quantify the differential impact of these characteristics on the subsequent speed of diffusion after initial trial. We conclude with caveats and suggestions for future research.

THEORETICAL FRAMEWORK

Based on hundreds of studies in various disciplines (e.g. sociology, education, marketing, and economics), Rogers (1983, p. 10) defines diffusion as the adoption of an innovation "over time among the members of a social system". Each individual within the social system is theoretically 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, when diffusion takes place across the different countries in the international community. The awareness and interest stages are difficult to directly measure, and may increasingly become invariant across countries due to the emergence of the "information age". Put differently, all countries/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

[3] Countries are defined broadly, in that they also include territories, protectorates or colonies, and United Nations members which are, however, often represented as being sovereign states in international agencies (e.g. the World

International Telecommunications Union, which regularly reports the existence of innovations to governments.

The Implementation Stage

In contrast to previously-published studies which focus on a comparison of within-country Bass-model (1969) diffusion parameters, we first want to understand the forces driving the start of a country's diffusion process, which logically *precedes* any subsequent within-country 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 the network technology in a given year, and the number of adopters predicted by the aggregate diffusion model of Easingwood, Mahajan and Muller (1983). The figure displays the familiar bell-shaped diffusion pattern. While it gives a parsimonious description of how fast the innovation will be accepted across the world, it does not help management to understand why certain countries adopt sooner than others. Indeed, the aggregate diffusion model used to make the forecasts ignores across-country differences 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 the probability of adoption to be heterogeneous across potential adopters (Chatterjee and Eliashberg 1990; Sinha and Chandrashekaran 1992). Moreover, since the unit of analysis is at the individual level, various causal factors which may affect the individual adoption decision can be included directly into the model and formally tested. Hannan and McDowell (1984), Sharma (1993), Sharma and Sinha (1991) and Sinha and Chandrashekaran (1992), for example, all investigated the impact of firm and market characteristics on the adoption timing of automated teller machines. We extend these approaches to the study of international diffusion processes, and study in a first stage the time until implementation for individual countries. In particular, our focus on the implementation stage allows us to consider the usefulness of Rogers' "innovator" or "laggard" spectrum when the individuals are countries. Does the profile of an innovative country differ from that of a laggard

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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).

country and, if so, what are the distinguishing features? We will address this question through a number of research hypotheses which we subsequently test in our empirical study.

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. In the second stage of the model, we again use an individual-level hazard model to understand what forces affect the rate at which different countries reach full confirmation, as reflected in a complete substitution of the old technology. Even though the implementation and confirmation stages clearly represent two distinct processes, they should not be studied in isolation, as they may affect each other. For example, later adopters may be able to "free-ride" on the innovators' experience with the technology, and as a result reach full confirmation earlier. In our model, we will allow, and empirically test for the existence of such interactions.[4] As discussed in the introduction, this second stage is also characterized by a substantial amount of variability across countries.

Research hypotheses

Our research hypotheses focus on extending diffusion theories to the global theater and are organized around four theoretical factors that influence the global diffusion of network technologies: (1) economic, (2) political, (3) social/demographic, and (4) network. While many of our hypotheses (those related to the first three factors) are applicable to innovations in general, some consider special characteristics of network technologies, as highlighted in the introduction. While the hypotheses are formally stated in terms of general constructs, we will also discuss the

[4] Conceptually, this second stage is similar to the *intra-organizational* diffusion process studied in Brettschneider and Wittmer (1993), Kim and Srivastava (1994) and Randles (1983), among others. Those studies focus attention on the rate at which, after the initial trial, an innovation gains acceptance within the organization, as measured e.g. by the level of penetration at any given point in time or the percentage of employees who have already switched to the new technology. In our second stage, attention is focused on the rate of adoption or substitution within a country, while the aforementioned studies used the organization as their social system of interest.

operationalization of these constructs as this is a critical issue in international studies where one needs to find globally representative proxies for over 160 countries.

Our first hypothesis simply states that a global diffusion process exists in both the implementation and confirmation stages. This is reflected by a time-dependent contagion effect describing a network technology's adoption across- and within-countries:

> **H1a:** The longer the duration since the first introduction of the network technology, the higher the probability of a given country adopting the network technology;
>
> **H1b:** The older the country's experience with the new network technology, the higher the probability of full confirmation.

In the context of micro-level diffusion models, these two contagion effects are empirically reflected in an increasing hazard rate (Mansfield 1968; Helsen and Schmittlein 1993). It is important to mention that here, our hypotheses do not only reflect an interpersonal influence, but also the impact of network externalities: as a network expands, there is increasing returns to other countries (or other regions within a country) in adopting the network technology as well (Arthur 1996)[5].

Our next hypothesis is also derived from the diffusion literature. Rogers (1983) notes that innovators tend to have a 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 diffusion rate are related to its standard of living and stage of economic development (Antonelli 1993; Gatignon and Robertson 1985). Following other authors (see, for example, Helsen et al. 1993), we use GNP per capita to measure a country's wealth, and hypothesize that wealthier countries will both adopt the new network technology and reach full confirmation sooner.

> **H2a:** A country's adoption timing, or innovativeness, is positively related to its GNP per capita, i.e. richer countries adopt earlier;

[5] Presumably, 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

H2b: Countries with higher GNP per capita reach full confirmation (replace the old network technology) sooner.

Here, we hypothesize that a country's wealth allows it to take higher risks (especially financial) in order to (fully) adopt a network technology, even if it does not benefit from network externalities as other countries have yet to adopt the new technology.

Our third hypothesis is based on several political-science and economic studies which argue that the planned economies of the Soviet Union and Eastern Europe tend to lag in the adoption of new technologies as members of their societies lack the economic incentives to innovate (see e.g. Amann and Cooper 1982; Berliner 1976; Leary and Thornton 1989). Also, these countries tend to have artificially isolated economies (i.e. would tend to benefit less from network externalities) which is an inhibitor of cross-country influence.

H3a: Adoption timing is negatively related to a country being currently or formerly governed by communist regimes;

H3b: Centrally planned economies who adopted the new network technology tend to reach full confirmation later.

Fourth, diffusion theory predicts that innovations diffuse slower in heterogeneous social systems as interpersonal influence processes are less effective (Gatignon and Robertson 1985). Thus, we expect that countries with heterogeneous social systems, for which we use their number of ethnic groups as a proxy, will tend to reach full confirmation later after the first system has been adopted. It is also natural to assume, since the implementation stage requires some sort of government/industry-wide coordination (e.g. standards and regulation) for which a social consensus needs to be reached, that social-system heterogeneity may negatively influence country adoption timing. In the context of a similar innovation in the digital-telecommunications industry (mobile telephones), Dekimpe et al. (1996) find support for this hypothesis: social heterogeneity tends to delay the implementation stage.

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countries with high quality networks grows, the remaining countries (or regions in a country) benefit more from joining the network.

H4a: The length of the implementation stage is positively related to the ethnic heterogeneity of the country;

H4b: The length of the confirmation stage is positively related to the ethnic heterogeneity of the country.

Our fifth hypothesis is related to the installed base of the old network technology. Three factors are to be considered: (1) the cost associated with the replacement of the old technology, (2) network externalities and (3) diffusion effects. As the cost of replacing the old technology increases with the size of the existing network, we hypothesize that full adoption (confirmation) of the new technology takes longer for these countries. The second factor, network externalities, influences both stages of the adoption process. The economics literature on network externalities (e.g. Katz and Shapiro 1985, 1986) 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 incentive for an individual to switch are smaller if the majority of potential communication partners are using the old technology and as a result the benefits of the new technology are significantly reduced. Said differently, the conversion of a larger installed base requires more coordination effort from the adopter population. We expect this "technological inertia" to affect both the implementation and confirmation phases.[6] Finally, for the implementation phase, diffusion theory proposes an alternative hypothesis: Rogers (1983) notes that heavy users of a technology tend to be innovators which suggests that larger networks would (partially) adopt the technology sooner. Larger countries, for example may find it less risky to try the technology on a small scale, versus smaller countries who might face replacing an entire network technology at the trial phase. In sum, for the confirmation stage different theories provide the same hypothesis while in the case of the implementation stage economic and diffusion theories provide contradicting predictions:

[6] While here we provide a rational 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 research on the diffusion of new product substitutes.

H5a: The length of the implementation phase is (a) positively related to the installed base of the old network technology if the theory on network externalities dominates or (b) negatively related to the installed base if diffusion theory dominates;

H5b: The length of the confirmation stage is positively related to the installed base of the old technology.

Our next hypothesis is motivated by managerial priors about compatible network technologies. A common belief among managers in industry is that eventually all countries will fully adopt new-generation network technologies, provided that these are deemed superior to existing systems by the early adopters. In aggregate diffusion models studying product substitution (of which new network technologies are a special case), this hypothesis is often used as a going assumption (Fisher and Pry 1971, Norton and Bass 1987, 1992).

H6a: Eventually, the new network technology will be adopted by each country;

H6b: The new network technology will fully replace the existing network technology in each country.

Our final hypothesis is about the linkage between the two processes. We expect that countries that are later adopters of the innovation can "free-ride" on the experience of earlier adopters with the network technology, and as a result, reach full confirmation earlier. For later adopters, the uncertainty associated with the new network 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 network technology. Prior empirical research provides support for this hypothesis. In their study on the diffusion of consumer durables in the Pacific Rim, Takada and Jain (1991) found that lagged adoption leads to an accelerated subsequent diffusion. Network effects also play a role for laggard countries. To the extent that communication also takes place across countries laggard countries benefit from a larger pool of countries whose network is based on the new technology.[7]

H7: The longer the implementation phase of a country, the shorter its confirmation stage.

We will now turn to the proposed model specification which is flexible enough to (1) allow for full substitution in the first year, (2) explicitly consider potential linkages between both processes, and (3) empirically test whether all countries will eventually adopt the new network technology and/or replace the older network technology entirely.

EMPIRICAL MODEL DEVELOPMENT

To explain the variability in both the timing of initial trial and the time needed to reach full substitution, a flexible split-population hazard model is used which (1) adjusts for the grouped nature of the data, (2) does not impose distributional assumptions with respect to the form of the baseline hazard, (3) incorporates both time-invariant and time-varying covariates, (4) corrects for unobserved heterogeneity, and (5) explicitly tests whether all countries will eventually adopt the innovation (i.e. start the implementation stage) and whether all will reach full substitution. Throughout the description of the model we will refer to the example of digital telephone switches to facilitate the exposition and also to make the connection to our empirical study easier.

The Split-population Model for the Implementation stage

Let T denote the random duration until a country adopts the innovation with probability density function $f(t)$, cumulative distribution function $F(t)$ and hazard function $\lambda(t)$. Yearly grouping intervals $[t_{k-1}, t_k)$, $k = 1, 2, ..., m+1$, $t_0=0$ and $t_{m+1}=\infty$ are defined, and the start of the adoption process (i.e. the installation of the first digital switch) in duration interval $[t_{k-1}, t_k)$ is recorded as t_k. This definition of discrete grouping intervals reflects the nature of our data: we

[7] This hypothesis is in contradiction with Rogers (1983) who says that earlier trial leads to deeper and faster adoption. This is true when the adopters are individuals, and the idea is partially captured by Hypotheses 1-4 which

know in what year a given country started the diffusion process, but do not know in what week or month this event took place. The innovation first became available in 1979, and a country starting the adoption process in this same year is given a duration of 1, in 1980 a duration of 2, etc. For the right-censored observations, i.e. countries which had not yet started the diffusion process by the end of the observation period, in our case 1993, a duration of 16 is recorded.

Parameter estimates are obtained through maximum-likelihood estimation, and the contribution to the likelihood function differs depending on whether or not a country had started the adoption process by the end of the observation period. The contribution to the likelihood function of country k which adopted the network technology in year t_k is given by $S(t_k\text{-}1)\text{-}S(t_k)$, where the survivor function $S(t_k) = 1\text{-}F(t_k)$ denotes the probability that the country has not yet adopted the new network technology after t_k years.[8] For country l which has not yet installed any digital switch by 1993 (i.e. the right-censored observations), the contribution to the likelihood function is given by $S(t_l\text{-}1)$; hence, $S(16\text{-}1)$ will denote that in the 15 years we observed the country, no trial was initiated. The contribution to the likelihood function of any country i can therefore be written as

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

where d_i is an indicator variable which takes the value of one if the country has not yet adopted by 1993, and zero otherwise.

To incorporate covariates into the model, we first develop an expression for the hazard function, and subsequently use a general relationship between a distribution's hazard and survivor function. Following Vanhuele et al. (1995), we write the hazard function $\lambda_i(t)$ as:

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

This expression consists of three building blocks. First, λ_0 gives the adoption rate of countries in the base group in the first year after the network technology's introduction. The base group is

predict a similar effect of the corresponding covariates for both processes. However, on the aggregate, we expect the experience and network effects described above to be stronger than the one mentioned by Rogers.

[8] By working with the difference of survivor functions rather than with the density function, we recognize the discrete nature of the yearly duration intervals. This adjustment is needed since not accounting for the discrete nature of the data has been shown to result in inconsistent parameter estimates, with increasing asymptotic bias as the grouping becomes more coarse (Kiefer 1988, Sharma and Sinha 1991).

defined as those countries for which all covariates, given by the vector $X_i(t)$, are zero. Second, when some of the covariates are different from zero, the country's hazard is multiplied by $e^{[\beta X_i(t)]}$. A positive β coefficient implies that an increase in the value of the associated covariate augments the adoption rate, or conversely, reduces the expected time until adoption. Finally, a set of time-varying dummy variables $D_i(t)$ is added to capture a wide variety of time dependencies. Consider, for example, the situation where a separate dummy variable is included for every possible adoption year. The dummy associated with year three is then always zero, except during year three when it takes the value of one. The vector of its different values over time is therefore given by (0 0 1 0 ...). To avoid identification problems when simultaneously estimating c_1 and λ_0, no dummy variable is included for the first year. As such, λ_0 reflects the adoption rate of the base group in the first period, and positive (negative) c-coefficients for the other intervals indicate a higher (lower) adoption rate compared to that first year. This approach makes no distributional assumption with respect to the nature of the time dependence, and is therefore called non-parametric (Vanhuele et al. 1995; Dekimpe and Degraeve 1996). The only assumption made is that within a grouping interval (e.g. a year) the hazard remains constant. Intuitively, this is equivalent to a piece-wise approximation of an underlying, possibly very complex, continuous time-dependence pattern. Its main advantage is that it results in consistent parameter estimates even when the true form of the baseline is unknown. In contrast, an incorrect parametric specification would result in inconsistent parameter estimates (Meyer 1990).

To estimate the parameters of interest, an expression for the survivor function $S_i(t)$ associated with the hazard in (2) is needed. Starting from the following general relationship (see e.g. Lancaster 1990) :

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

and assuming that all time-varying covariates remain constant within a given year, but are allowed to change from year to year, it is easy to show (see e.g. Vanhuele et al. 1995) that:

$$S_i(t) = e^{-\lambda_0 B_i(t)}, \text{ where } B_i(t) = \Sigma_{j=1}^{t} e^{\beta X_i(j) + cD_i(j)} \tag{4}$$

and the corresponding log-likelihood function for N countries becomes:

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

In Equation (5), we implicitly assume that every country in the base group has the same initial adoption rate λ_0. However, some of the factors that can have an impact on a country's adoption timing may be hard to quantify (e.g. the attitude of its political leaders towards innovations), or may not have been available in our data set (e.g. the number of political parties forming the government). Not accounting for this unobserved heterogeneity has been shown to cause a spurious negative duration dependence, and to result in inconsistent parameter estimates for the included covariates (see e.g. Lancaster 1990). To correct for the presence of unobserved heterogeneity, we follow Gupta (1991) and Vanhuele et al. (1995), and let λ_0 be distributed according to a gamma mixing distribution. This mixing distribution is quite flexible, and has been shown to result in the following closed-form solution for the log-likelihood function (see Vanhuele et al. 1995 for a formal proof):

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

The average first-year adoption rate for countries in the base group is then given by the mean of the mixing distribution, r/a, and all other coefficients can be interpreted relative to this ratio in the same way as they were interpreted vis-à-vis λ_0 in the earlier models.

Thus far, we assumed that every country will eventually try the new network technology. To empirically validate this assumption, a split-population extension of the model in Equation (5) is used in which we assume that the population of countries consists of two sub-populations: a group of eventual adopters, and a group who will never adopt. The relative size of both groups is indicated by, respectively, δ and $(1 - \delta)$, and the hazard model in equation (5) is assumed to only apply to the former group. Intuitively, this approach allows for a discrete spike at $\lambda_0 = 0$, and the magnitude of this spike (i.e. $1 - \delta$) indicates how many countries will not try the product even as $t \rightarrow \infty$. If δ gives the (homogenous) probability of belonging to the group of eventual adopters, the likelihood function for N countries becomes (see Sinha and Chandrashekaran 1992 for a detailed discussion):

$$L = \Pi_{i=1}^{N} \{\delta[S_i(t_i - 1) - S_i(t_i)]\}^{1-di} * \{(1-\delta) + \delta S_i(t_i - 1)\}^{di} \tag{7}$$

If all countries which will eventually adopt have the same λ_0, one can substitute Eq. (4) into (7) to derive a split-hazard model which does not yet correct for unobserved heterogeneity among the eventual adopters. In order to account for this heterogeneity, we again let λ_0 be distributed according to a gamma mixing distribution. This results in the following expression for the log-likelihood function (Dekimpe et al. 1995; Van de Gucht 1994):

$$LL = \Sigma_{i=1}^{N} \ln\{\frac{(\delta^{1-di} - \delta)(1+d_i)a^r}{[(1-d_i)B_i(t_i - 1) + a]^r} - \frac{(\delta^{1-di} - \delta)a^r}{[(1-d_i)B_i(t_i) + a]^r} + \tag{8}$$

$$\frac{\delta(1+d_i)a^r}{[B_i(t_i - 1) + a]^r} - \frac{\delta a^r}{[B_i(t_i - 1) + (1-d_i)e^{\beta Xi(ti) + cDi(ti)} + a]^r}.$$

The Split-population Model for the Confirmation Stage

The model used in the confirmation stage is similar to the model described in the previous section. The only differences are that (1) the relevant duration T is now given by the number of years elapsed between the implementation stage (i.e. the year the first digital switch is installed) and the year when full substitution is obtained, and (2) the sample is limited to those countries which have initiated the diffusion process. As the countries' trial year varies widely (see Figure 1), the starting point for the computation of this second duration also differs across countries. Even though this slightly complicates the construction of the data matrix, it does not alter the resulting model specification. For a country which implemented the first digital switch in 1987 and reached full substitution in 1989, a duration of 3 is recorded. This same duration is obtained for a country which started the trial stage in 1989 and replaced the last analogue switch in 1991. Special care is also needed when dealing with time-varying covariates and control variables. For example, for the former country, the relevant control variable "size of the installed base" in the computation of $\lambda(1)$ is the number of analogue lines at the end of 1986 (i.e. at the end of the preceding year), while for the latter country one should use the number of analogue lines at the end of 1988. For countries which have not yet reached full substitution by the end of the observation period, a censored duration is computed in much the same way as described in the previous section. Finally, it is worth indicating that in this stage, the model parameter δ will test the underlying assumption of the Fisher and Pry (1971) and Norton and Bass (1987)-model that the new network technology will eventually drive the older network technology out of the market in all countries.

EMPIRICAL STUDY

We now turn to an empirical application of the proposed modeling approach to data collected on the trial and confirmation of digital telephony. While the observed differences across countries in this network technology's diffusion patterns may also be affected by a variety of *industry-specific* characteristics, we focus in this study on four *general* factors suggested in the extant literature and described in the introduction: (1) economic, (2) political, (3) social/demographic, and (4) network. We will test these hypotheses using covariates collected on 162 countries.

The 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 countries (12) which had not yet started the adoption process, the common censoring date was 1993. For the time until full substitution, 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 before), while 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, on the other hand, the percentage substituted in 1993 (66%) was available, and 1993 was taken to be the censoring point for that country. As such, we take a conservative approach in that 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, in that 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 size of the installed base of the old technology is measured differently in the implementation and confirmation stages. In the implementation stage of the model, the size of the telephone network at the end of the preceding period is used. For example, the hazard rate in period one (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, etc. For the confirmation stage, on the other hand, the number of lines *not yet serviced* through digital switches is computed in every period. In doing so, we account for the fact that as the confirmation stage progresses, the remaining installed base of the old network technology gradually becomes smaller.

Data on the explanatory variables were collected from Euromonitor Ltd. and the *World Factbook* (Central Intelligence Agency, 1993). One of them is time-varying, i.e. the size of the existing telephone network. All other covariates are treated as time-invariant, i.e. we assume that they did not vary in a systematic fashion over the considered time span. Relevant summary statistics are presented in Table 2, 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 international researchers are well aware of, it is very difficult to find globally representative proxies for over 160 countries. As such, some variables which could potentially have an impact were not included in the model because their values were only available for a small fraction of the countries. This limitation underscores the importance of correcting for unobserved heterogeneity.

The nature of political system is represented with a dummy variable (1 if the country had a communist regime during most of the observation window, and 0 otherwise). None of the (ex-) communist countries had reached full substitution by the end of the observation period. Because of the resulting lack of within-sample variability, it was not possible to obtain a reliable estimate for this covariate. The split-hazard model for the confirmation stage was therefore estimated for the 134 non-communist countries which were not censored in the first-stage model, i.e. which had started the adoption process.

Analysis

Baseline Specification. Maximum-likelihood estimates for both stages are given in Table 3. When applying a piece-wise approximation to an underlying continuous baseline hazard, it is important to determine the number and location of the discrete shifts. Given the limited sample size (N_1=162; N_2= 134), and the variability in adoption durations (ranging from 1 to 15), it did not make sense to allow for a different *c*-parameter in every year. Initially, a model was estimated in which we allowed for a discrete shift after every two years, i.e. we imposed the restriction that within that time span the base adoption rate remained constant. Likelihood-ratio tests were subsequently used (1) to assess the validity of this assumption, and (2) to subsequently determine whether adjacent time spans could be combined to reduce the number of parameters which needed to be estimated. Detailed results on these likelihood-ratio tests are available from the authors upon request. For the confirmation stage of the model, no completed events were observed with a duration greater than 7 (even though some of the censored observations had a larger duration). This precluded the estimation of a separate *c*-parameter for these periods, and we imposed the restriction that the baseline hazard in period 7 equaled the baseline hazard in the subsequent periods.

Hypothesis Tests

The baseline hazard in Figure 2A clearly illustrates the "snowball effect" (Helsen and Schmittlein 1993) resulting mainly from the reduced uncertainty as time elapses and more countries around the world adopt the innovation. An international contagion effect, or **H1a,** is therefore supported: the longer the duration since the introduction of the innovation, the higher the probability of a given country adopting the innovation. For the within-country diffusion process (**H1b**), our findings are mixed. As illustrated in Figure 2B, we find that if a country does not immediately adopt to 100% in the first year, the baseline hazard actually drops in year 2. This phenomenon may reflect the duality observed by Utterbach (1994) in the context of new technology adoptions by firms. Some make "a clean break" from existing systems (which would translate to an immediate full substitution), while others do so in a gradual ("halfhearted") way. Clearly, own experience and/or network effects do not affect the adoption speed of the former sub-population, but do affect the speed with which the latter subgroup will eventually reach full substitution, as is reflected in the increasing baseline hazard as time elapses. Put differently, the convex baseline hazard may provide evidence for the existence of two different sub-groups in the population, those following the "clean-break strategy" and those following the "dual-system" strategy (Utterbach 1994), with the time dependence affecting only the latter. Furthermore, this finding also illustrates the importance of working with a non-parametric baseline specification, as such time dependence would not have been easily picked up by most of the commonly-used parametric forms (such as the Weibull or Gompertz specifications). Finally, even though we only imposed a restriction on the baseline hazard from period 7 onwards (see before), we see that the likelihood-ratio tests already support a constant hazard rate from period 5 onwards.

We now turn to factors which stand to cross-sectionally characterize the implementation and confirmation stages. Table 3 reports the results of our tests of Hypotheses **H2-H7**. **H2** hypothesizes that a faster implementation and confirmation process can be expected for wealthier countries. We find that richer countries adopt sooner (**H2a** is supported), but this effect is not significant for the confirmation phase (**H2b** is not supported). The former finding is in line with previous findings in the context of cellular telecommunications (Dekimpe et al. 1996) and the latter finding may be due to the fact that poorer countries tend to be laggards (see **H2a**) and thus benefit from the experience of earlier adopters. The strong support for **H7** (see below) further confirms this intuition. **H3** states that the implementation and confirmation stages are negatively related to a country being currently or formerly governed by communist regimes. The fact that none of the (ex-) communist countries had yet reached full substitution by the end of the observation period (cf. supra), provides support for **H3b**. The impact of the communism variable on the length of the implementation stage (**H3a**), on the other hand, while directionally correct, is not statistically significant. **H4a** argues that the ethnic heterogeneity of a country is positively related to the length of the implementation phase. We find some support ($p < 0.11$) for this hypothesis. **H4b** states that the length of the confirmation stage is positively related to the country's ethnic heterogeneity. This hypothesis is strongly supported confirming the conjecture by Gatignon and Robertson (1985). **H5a** highlights conflicting views in the literature. According to the literature on network externalities the implementation phase should be longer for countries with a large installed base, while diffusion theory would suggest the opposite. The data do not suggest the dominance of either theory on another. In **H5b**, we hypothesized that the confirmation stage is longer for countries with large installed bases. This hypothesis is strongly supported by the data and nicely illustrates the importance of "technological inertia" for network products underlined in the literature. Our final hypotheses are concerned with some general conclusions on the global diffusion process of network technologies. Based on industry-wide managerial intuition, in **H6**, we hypothesized that eventually all countries will try and fully replace the old network technology with the innovation. Support was found for both **H6a** and **H6b**: in the implementation model, the δ parameter quickly converged to 1.0, while the point estimate in the confirmation stage (i.e. 0.79) was not significantly different from one.[9] Not only will all countries try the network technology, it is also found that all analogue switches will eventually be replaced by digital ones in each country of the world. Finally, we also tested the linkage between the two phases of the global diffusion process, and found that later adopters tend to reach full confirmation earlier, thereby obtaining support for **H7**. It seems that later adopters benefit from earlier adopters' experience which reduces the uncertainty surrounding the innovation, thus leading to a faster acceptance rate.

Robustness tests

In order to test the robustness and validity of our findings, we conducted a number of supplemental tests. In all cases, we were interested in knowing whether the hypothesis tests were affected by the implementation reported.

First, we estimated the following competing parametric specifications for both the implementation and confirmation stages: (1) a split-population model with a Gompertz baseline hazard, and (2) a regular, non-split model with a quadratic baseline specification. In all four instances, our non-parametric specification resulted in a better fit, as illustrated in Table 4. In the implementation stage, the linear trend term was significant and positive for both the split-Gompertz and the quadratic specification, which confirms the snow-ball effect we illustrated in Figure 2A (cf. **H1a**). The quadratic term in the latter specification, on the other hand, was not significant. In the confirmation stage, we obtained a (significant) negative linear and a (significant) positive quadratic term, which captures the convexity observed in Figure 2B (cf. **H1b**).

As discussed in Helsen and Schmittlein (1993), the quadratic duration distribution is defective when the quadratic term is negative and significant, implying that the quadratic specification provides an alternative test of **H6** (for identification purposes, we did not combine the

[9] While one should be careful in the interpretation of this likelihood-ratio statistic as it tests for a value on the boundary of the parameter space, its value is sufficiently small not to reject the null hypothesis (see also Schmidt and Witte 1989).

split-hazard property with a quadratic baseline). This was the case for neither the implementation (where the quadratic term was insignificant) nor for the confirmation stage (where the quadratic term was positive). Hence, the same substantive conclusion, i.e. that eventually all countries will adopt the new network technology and fully substitute the old network technology, was obtained using both a non-parametric split-hazard approach and a regular hazard model with a potentially defective parametric duration distribution. We also compared the split-Gompertz specification (cf. Table 4) against a regular hazard model with Gompertz baseline. In both instances the proportion of eventual adopters (δ) converged to 1.0, providing further support for, respectively, **H6a** and **H6b**.

To validate our findings for the implementation stage, we assessed their sensitivity to the length of the observation interval. Specifically, we assessed whether the same conclusions would have been obtained if the censoring point had occurred in 1991 and 1992 rather than in 1993. In doing so, the number of censored observations increased to, respectively, 16 (in 1992) and 32 (in 1991). All parameter estimates were very robust to these modifications, as illustrated in Table 5. Especially noteworthy is that already in 1991, when the number of censored observations was substantially larger than in the original estimation, the model predicted that eventually all countries would implement the new network technology.

Thus far, we defined confirmation as a 100% substitution rate, which clearly is a fairly stringent criterion. One could also consider the time needed to reach 90 percent substitution, which corresponds to the take-over time in Fisher and Pry's (1971) specification. This less stringent definition of confirmation resulted in 13 additional completed durations, as 13 countries had already reached 90% substitution by the end of the observation period, but had not yet managed to reach full substitution. The resulting parameter estimates for this operationalization of the confirmation stage are given in Table 6. Again, the same substantive conclusions as before were obtained, i.e. a convex baseline hazard (**H1b**), a longer confirmation stage for heterogeneous countries (**H4b**), faster substitution for later adopters (**H7**) and countries with smaller installed bases (**H5b**), while all countries are predicted to eventually reach 90% substitution (**H6b**). Moreover, when estimating the split-Gompertz model on this data set, the δ-parameter again converged to 1.0 for this parametric specification, and the same conclusion on the long-run percentage of countries reaching confirmation was unambiguously obtained in three different model specifications: the non-parametric split, the split-Gompertz and the regular quadratic model.

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 cross-country diffusion takes place in two distinct, although related, phases: the implementation or trial stage and the confirmation stage. This paper proposes a double-hazard approach to model this process, and tests research hypotheses generated from the extant literature. Our objective was to understand diffusion dynamics of a special product category, network technologies, which require that diffusion theory and the resulting models be adapted to take into account the effects of network externalities, such as the potential for a non-S-shaped diffusion pattern within some countries, and the considerable impact of the installed base.

Our empirical results provide interesting theoretical insights and have important managerial implications. First, we find strong international contagion effects: the more countries that have adopted, or the longer the international experience the world has 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), and characterized by a more homogeneous social system (confirming Dekimpe et al.'s (1996) finding for cellular telephones). At the confirmation phase, we find that countries with homogeneous social systems reach full confirmation faster (as hypothesized by Gatignon and Robertson, 1985). We also find that laggard countries have faster within-country diffusion rates (consistent with Takada and Jain 1991). For the confirmation stage, our data provide strong evidence for the existence of network externalities: the large installed base of some countries exert a negative effect on the diffusion of a new network technology. As none of the ex-communist countries had yet reached full substitution by the end of the observation period, we also found evidence for the slower diffusion of new technologies in those countries. In terms of the long-run acceptance/substitution probabilities, several model specifications confirmed the managerial intuition that eventually every country will both accept the new network technology and fully replace the old network technology.

Some of our hypotheses were not confirmed, however, and require further theoretical and/or empirical investigation. We find, for example that the speed of the within-country diffusion is not affected by the wealth of a country. As noted before, this result may come from the fact that poorer countries tend to be laggards (try the new technology later) and, as a result, may benefit more from the experience of other countries. Given the importance of emerging international communication networks (e.g. Internet and other on-line services, World-Wide-Web, etc.) further empirical research in this area is warranted.

Our empirical findings are based on the observed diffusion process of one high-technology industrial product. Our modeling approach is general, however, and with minor modifications it is applicable to the global diffusion of all product innovations. For instance, 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 instances, as in this particular application, diffusion is of a *decentralized* nature where the manufacturers themselves do not determine when sales will begin in a specific country, but where foreign governments determine (even though the firms may try to influence that decision) from what point the innovation is, respectively, 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 and their governments, rather than of the individual network technology providers like Alcatel, AT&T, Ericsson, or Siemens.[10] Future research which considers centralized diffusion processes, using the modeling approach presented, may find support for some of the hypotheses presented and lead, therefore, to greater insights into globalization patterns.

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

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Table 1: Network Adoption Timing (*Percentages*)

Country	t 1	t 2	t 3	t 4
A	0	100	100	100
B	10	20	40	80
C	100	100	100	100
D	0	0	10	20

Note: The figures indicate the percent of the old technology replaced by the new technology. A non-zero number indicates trial (implementation), while full-adoption (confirmation) is reflected by 100%.

Table 2A: Summary statistics - Implementation stage (N=162)

Covariate	Mean	STDV	Minimum	Maximum
Economic factor				
GNP/Capita	4,381.3	6,554.6	71.0	30,304.0
Political factor				
Communism	0.1	0.3	0.0	1.0
Social/Demographic factor				
Ethnic groups	5.1	2.6	1.0	15.0
Network factor				
Analog lines in 1978 (000)	1,845.4	8,734.9	0.3	99,449.48
Year of implementation	NA	NA	NA	NA

Table 2B: Summary statistics - Confirmation stage (N=134)

Covariate	Mean	STDV	Minimum	Maximum
Economic factor				
GNP/Capita	4,889.6	7,039.8	71.0	30,304.0
Political factor				
Communism	NA	NA	NA	NA
Social/Demographic factor				
Ethnic groups	5.0	2.6	1.0	14.0
Network factor				
Analog lines in T^{*}-1 (000)	2,730.5	11,655.5	2	122,203.0
Year of implementation	1988.0	3.1	1980	1993

NA = Not Applicable;
T^{*} - 1 = the year preceding the start of the implementation stage

Table 3A
Parameter estimates - Implementation stage

Time dependence (H1a)	
r/a	0.0025
c_3 -- c_7	2.26^{**}
c_8 -- c_{11}	4.09^{**}
c_{12} -- ...	5.36^{**}
Economic factor (H2a)	
GNP/Capita ($ 0,000)	0.65^{***}
Political factor (H3a)	
(former) communist country	-0.21
Social/Demographic factor (H4a)	
Ethnic groups	-0.05^{*}
Network factor (H5a)	
Number of lines in t-1 (000,000)	0.00
Full adoption (H6a)	
δ (proportion of ultimate adopters)	1.0[a]

***: $p < 0.01$ (one-sided test)
** : $p < 0.05$ (two-sided test)
* : $p < 0.11$ (one-sided test)

a: not significantly different from 1.0;

LL = -387.58; $AIC = LL$ - (number of estimated parameters) = -397.58.

Table 3B
Parameter estimates - Confirmation stage

Time dependence (H1b)	
r/a	0.004
c_2 --c_4	-1.55*
c_5 -- ...	0.35
Economic factor (H2b)	
GNP/Capita ($ 0,000)	0.26
Political factor (H3b)	
(former) communist country	NA
Social/Demographic factor (H4b)	
Ethnic groups	-0.23**
Network factor (H5b)	
Number of analogue lines in t-1 (000,000)	-0.98***
Full adoption (H6b)	
δ (proportion reaching full substitution in the long run)	0.79[a]
Adoption timing (H7)	
Year of implementation - 1979	0.49***

***: $p < 0.01$ (one-sided)
** : $p < 0.025$ (one sided)
* : $p < 0.05$ (two-sided)

a: not significantly different from 1.0;

LL = -78.95; AIC = -87.95;

NA = Not applicable;

Table 4
Competing model specifications

	STAGE 1 IMPLEMENTATION STAGE		STAGE 2 CONFIRMATION STAGE	
Model	LL (# parameters)	AIC	LL (# parameters)	AIC
Split-Gompertz	-395.69 (8)	-403.69	-82.32 (8)	-90.32
Regular quadratic	-396.59 (8)	-404.59	-82.07 (8)	-90.07
Non-parametric split	-387.58 (10)	-397.58	-78.95 (9)	-87.95

AIC = log(maximum likelihood)-(number of estimated parameters). Larger values indicate more preferred model.

Table 5
Sensitivity of the parameter estimates to the censoring year

	1993	1992	1991
Time dependence (H1a)			
r/a	0.0025	0.0024	0.0025
c_3 -- c_7	2.26**	2.26**	2.26**
c_8 -- c_{11}	4.09**	4.09**	4.10**
c_{12} -- ...	5.36**	5.40**	5.30**
Economic factor (H2a)			
GNP/Capita ($000)	0.65**	0.66**	0.68**
Political factor (H3a)			
(former) communist country	-0.21	-0.25	-0.18
Social/Demographic factor (H4a)			
Ethnic groups	-0.05*	-0.04	-0.05*
Network factor (H5a)			
Number of lines in t-1 (000,000)	0.00	0.00	0.00
Full adoption (H6a)			
δ (proportion of ultimate adopters)	1.0[a]	1.0[a]	1.0[a]

***: $p < 0.01$ (one-sided tests);
** : $p < 0.05$ (two-sided tests);
* : $p < 0.15$ (one sided test);

a: not significantly different from 1.0;

Table 6
Parameter estimates when confirmation = 90 % substitution

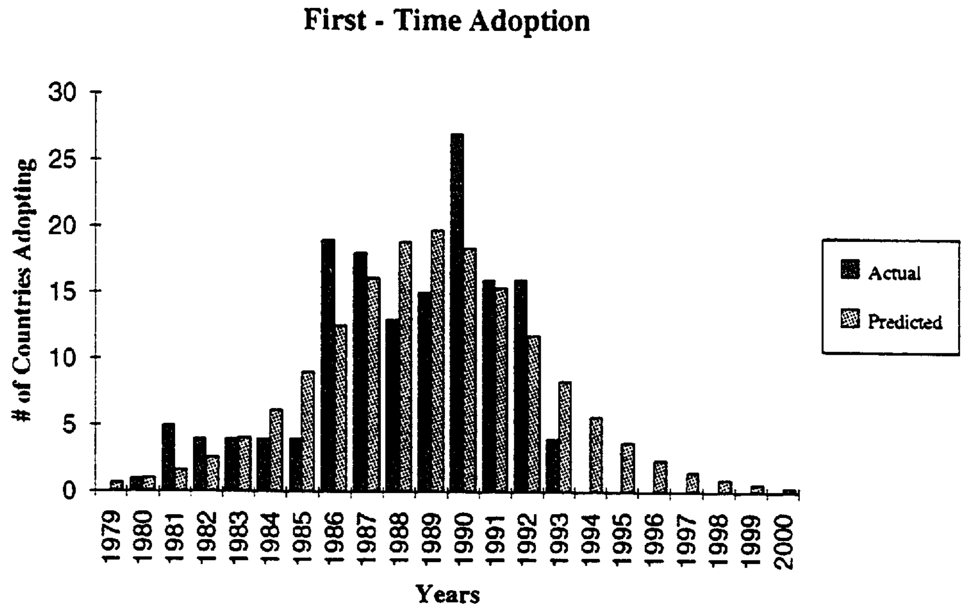
Time dependence (H1b)	
r/a	0.01
c_2 -- c_6	-1.31^{b}
c_7 -- ...	0.62
Economic factor (H2b)	
GNP/Capita ($000)	0.01
Political factor (H3b)	
(former) communist country	NA
Social/Demographic factor (H4b)	
Ethnic groups	-0.10^{*}
Network factor (H5b)	
Number of analogue lines in t-1 (000,000)	-0.15^{**}
Full adoption (H6b)	
δ (proportion reaching 90% substitution in the long run)	1.0^{a}
Adoption timing (H7)	
Year of implementation -1979	0.33^{**}

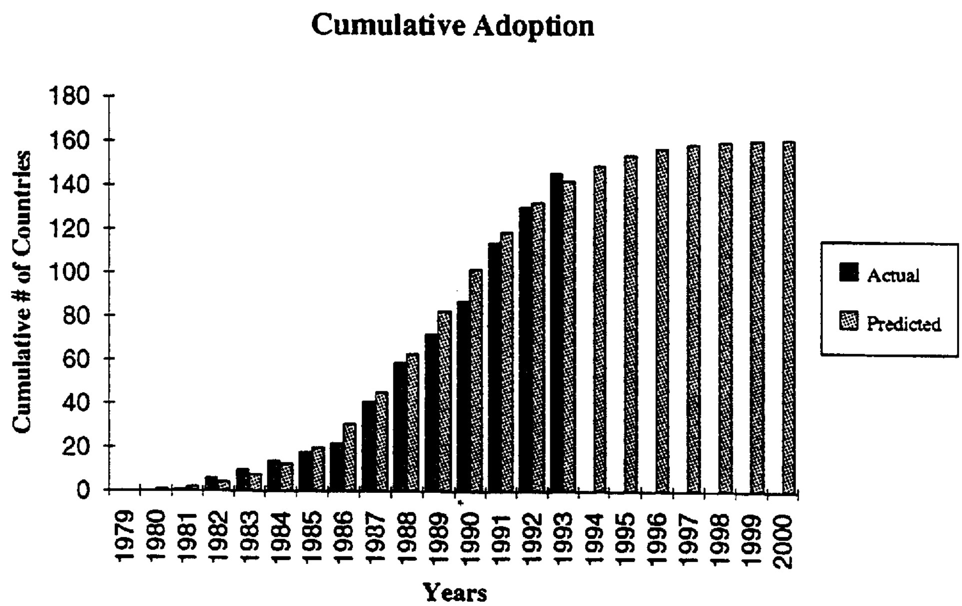
***: $p < 0.01$;
**: $p < 0.025$;
*: $p < 0.1$;

a: not significantly different from 1.0;
b: $p < 0.05$ (two-sided test)

LL = -118.79; AIC = -127.79; NA = Not applicable;

Figure 1: Variability in Trial Time





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

Figure 2: Time dependence

Figure 2A: Implementation Stage

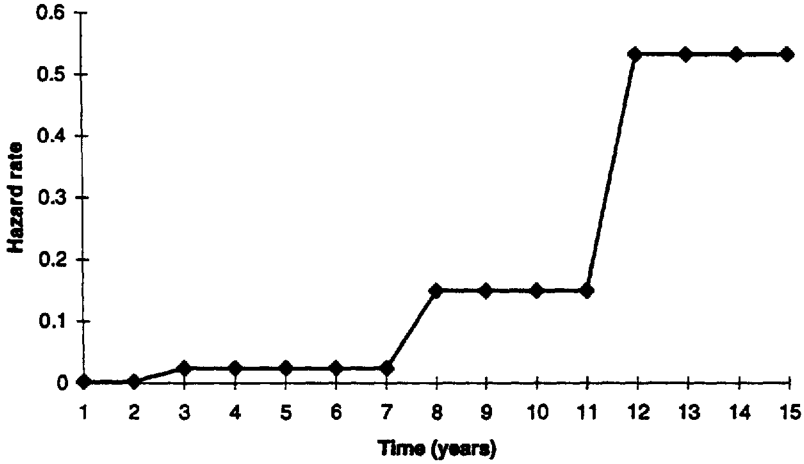


Figure 2B: Confirmation stage