"GLOBALIZATION": MODELING TECHNOLOGY ADOPTION TIMING ACROSS COUNTRIES

by

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98/69/MKT
(Revised Version of 97/75/MKT)

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Printed at INSEAD, Fontainebleau, France.

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June, 1998

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

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Abstract

We study global adoption processes where the units of observation are countries which sequentially adopt a particular innovation. Our goal is to provide a better understanding of how exogenous and endogenous country characteristics affect this diffusion process. We develop a general model of global adoption processes that allows researchers to test extant theories of cross-country adoption, and illustrate the approach using data from the cellular telephone industry for 184 countries. In our application, we find support for the existence of a global "demonstration effect": as the number of countries adopting the technology becomes larger, the likelihood of "similar" countries following their example increases. We also find that isolated economies lag in adopting technologies, and that countries with homogenous and concentrated populations, and with a high level of economic development are, on average, earlier adopters. Finally, our model supports the managerial intuition that, eventually, all countries will adopt cellular technology.

1. INTRODUCTION

Virtually every textbook on international or global marketing has a chapter on international segmentation strategies. The discussions in these focus on various criteria upon which managers can cluster countries into homogenous units within which uniform strategies can be developed. These criteria often involve economic, cultural, or social dispositions. Few, if any, consider the countries' *adoption timing* as a fundamental segmentation criterion. Still, the global or worldwide diffusion of any technology implies its adoption by over 180 countries, some of which will initiate the adoption process considerably sooner than others. A basic understanding of factors likely to affect the timing of a country "adopting", or allowing the importation of, a given technology is of crucial interest to managers who face dynamic operational and/or resource-allocation decisions, or who have to establish strategic priorities for their international expansion process. Indeed, knowing that a country will have a large market potential and fast penetration rate may be inconsequential to planning if the country will only begin adoption well beyond the firm's typical planning horizon (e.g. 10 to 15 years after the technology is originally introduced to the international community). Moreover, different marketing strategies may be called for to stimulate the subsequent within-country diffusion pattern for early versus late adopters (see e.g. Mahajan et al. 1990; Ganesh and Kumar 1996; Lee 1990), and the time differentiation in adoption may partially explain the often-observed international product life cycle, whose implications for international trade and business have been well documented (see e.g. Ayal 1981; Vernon 1979).

The goal of this paper is to explain *why* certain countries adopt (try) a technology sooner than others[1]. In other words, which country characteristics affect whether and to what extent a certain country will emerge as an "innovator" (early adopter) or a "laggard" (late adopter) in adopting a new technology? Building on previous work, we extend diffusion theory to the global marketing context where the unit of analysis (the adopting entity) is a country. Our approach recognizes the difference between consumers and countries as adopting units. In particular, for most new products and services (e.g. technological products, drugs, food, etc.) the adoption (trial) decision of a country critically depends on some "agreement" or "consensus" between social system members. This often involves the coordinating activity of a regulatory agency or the government which sets standards and

[1] As it will become clear later, we mean by adoption that a country tries the technology or innovation. In this sense, adoption occurs when the first application of the innovation appears in the country.

regulations. While consumers and firms influence the decision process, it is ultimately an organization or a bureaucracy representing the social system's members that makes the decision. We investigate how country (social system) characteristics affect the adoption decision process under this scenario.

Our empirical investigation considers three general classes of *exogenous* factors which are of interest to international marketers, and which will ultimately affect the adoption decision: (1) country demographic factors, (2) economic/political factors, and (3) social factors. We also investigate the impact of *endogenous* factors, such as the elapsed time since the introduction of the innovation (a proxy for the accumulated experience with the innovation) on the adoption timing of the remaining countries, a phenomenon called the demonstration effect. In addition, we test for the existence of any incremental demonstration effect emanating from "similar" countries. Besides hypotheses based on academic research, in our empirical application, we also assess the validity of an industry-specific managerial intuition, namely the conjecture that eventually all the countries of the world will adopt the innovation. Apart from identifying *which* country characteristics affect adoption timing (as well as the direction of their effect), we will also assess their *relative importance* in explaining "country innovativeness". In this way, we hope to provide managers with guidelines on the variables to consider when segmenting international markets for the introduction of new technologies/products.

The remainder of the paper is organized as follows. In Section 2, we extend diffusion theory to the international marketing context, and develop hypotheses concerning the effects of country characteristics on the adoption timing of a country. In Section 3, we propose a flexible methodology to empirically test these hypotheses. In section 4, we apply the model in the context of a specific innovation, cellular telecommunication services, and conclude in Section 5 with a discussion on managerial implications, implementation issues, and areas for future research.

2. CONCEPTUAL FRAMEWORK

2.1 Diffusion theory in an international marketing context

The basic idea underlying diffusion theory is that (potential) adopters of an innovation do not adopt the innovation independently, but instead influence each others' adoption decisions. In the context of consumers, for example, the more consumers have adopted the innovation, the higher the

likelihood that the remaining consumers will also do so. The influence of early adopters (innovators) on later adopters (laggards) is often called "word of mouth communication" (Rogers, 1983), a term referring to a much broader set of phenomena than consumers simply talking to each other. For instance, a consumer might be influenced by another consumer simply by observing his/her behavior. Similarly, when the adopting units are firms, the uncertainty surrounding a firm's adoption of a technological innovation may be reduced when observing other firms' experiences (Ganesh and Kumar 1996).

In this paper, we extend the diffusion paradigm to an international marketing context by assuming that a similar (broadly defined) communication process exists across countries as has been observed between consumers (Gatignon and Robertson 1985) and organizations (Sinha and Chandrashekaran 1992; Ganesh and Kumar 1996). This process is in part the result of the micro-level communication processes between the individual countries' consumers (Mahajan and Muller 1994, Putsis et. al. 1997). For many products and services, however, the adoption decision, although strongly influenced by local consumers, is ultimately made by a regulatory agency or the government. In the case of telecommunications innovations, for instance, the local PTTs (in most European countries) or other agencies (e.g. the FCC in the US) have to decide on standards and regulations before consumers have access to any service. While the importance of such an agency in the adoption decision clearly varies across products, its coordinating role is critical for a large number of categories including medical products, food and chemicals, energy-supply systems, telecommunication services, and many others. Thus, beyond traditional consumer interactions, the communication process driving diffusion across countries is also a function of communication between governments (as it is between organizations in explaining industrial adoption processes) and the extent to which a consensus can be reached within a social system (see e.g. Robertson and Wind 1980).[2]

Recognizing the role of a central decision making unit for the introduction of the innovation in a particular country is important because it basically means that the *trial* of the innovation by a certain country and its subsequent *diffusion within the country* are governed by fundamentally different processes, as they involve different decision making units (DMUs). While the trial phase is mostly determined by the characteristics of a bureaucracy and its relation to the consumers it represents,

[2] While we argue that a country is a qualitatively different decision-making unit, and draw upon this difference to generate our hypotheses, we do not explicitly study the decision process itself, mainly because we do not have data on the appropriate institutional details and legal contexts on a worldwide basis.

within-country diffusion is directly influenced by the characteristics of the consumers themselves.[3] To illustrate the applied importance of this idea, consider Figure 1 which shows the aggregate adoption of cellular telephone services (subscriptions) on a worldwide basis. While one might be tempted to directly explain the dynamics of this aggregate diffusion process, this curve inherently masks two underlying, yet fundamentally different, processes:

- the adoption time *across* countries, i.e. when will the innovation first appear in an individual country, and
- the *within-country* diffusion process, i.e. given the adoption time, what is the innovation's likely diffusion pattern within a country?

We label these two processes the *breadth* and *depth* of adoption, respectively. Beyond the above mentioned theoretical consideration (different DMU), there is also a pragmatic reason why one might want to distinguish between breadth and depth of the global diffusion process: the data describing the two sub-processes are typically of a different nature, which implies that different statistical tools are appropriate for studying them. While for the breadth dimension it is relatively easy to obtain dis-aggregate data (allowing the application of micro-level diffusion models, e.g. Chatterjee and Eliashberg 1990), the depth process is almost always described by aggregate data (calling for an aggregate, Bass-type (1969) diffusion model).

The focus of the present paper is on the breadth dimension of the diffusion process for two reasons. First, while the breadth process is a critical necessary condition to the depth process, it has received little attention in the international marketing literature.[4] Second, as it involves a different decision making unit, it raises an interesting theoretical challenge for the application of the diffusion paradigm and the development of formal research hypotheses. The role of the next section is to undertake this challenge.

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[3] Similarly, an organization's decision-making unit (e.g. the buying center) typically has to decide on the adoption of a technological innovation before the actual *intra*-organizational diffusion among its employees can start (see Levin et al. 1987 and Kim and Srivastava 1994).

[4] Depth processes (i.e. within-country diffusion dynamics) have been considered in numerous marketing studies including Dekimpe, Parker and Sarvary 1997, Ganesh and Kumar 1996, Gatignon, Eliashberg and Robertson 1989, Helsen et al. 1993, Putsis et. al. 1997, Takada and Jain 1991 and Mahajan and Muller 1994. Even though Lee (1990) emphasized the timing (or breadth) dimension, he also used a depth measure (the proportion of within-country adopters at a fixed point in time) to study international innovativeness.

2.2 Research hypotheses

In this section, we develop formal research hypotheses on how country characteristics influence the diffusion process across countries. In doing so, we recognize that the general hypotheses developed here need to be put in context when a specific real-life application is sought. In particular, any application of the general theory will have to take into account (1) the specific product considered, and, (2) the availability of appropriate data (Lynn and Gelb 1996, Putsis et. al. 1997). Indeed, the product context will largely influence how certain theoretical constructs (such as "relative advantage", for instance) will be operationalized. Factors idiosyncratic to the product context might also call for different control variables (e.g. international trade agreements applying to the category, etc.). Similarly, the availability of data for over 180 countries of the world will influence which hypotheses can be tested in the first place. Data availability will also impact what proxies might be used to capture some theoretical constructs (e.g. the "wealth" of a country). In sum, the hypotheses below need to be further refined in any empirical application, as illustrated in Section 4.1.

Our first hypothesis simply states the existence of a demonstration effect. This hypothesis basically says that an international diffusion process exists, i.e. that for countries which will eventually adopt the innovation, the adoption timing of a country is not independent from those of other countries. In the context of international diffusion, we theorize that this demonstration effect is in part a result of traditional communication processes between the countries' consumers (e.g. Mahajan and Muller 1994, Putsis et. al. 1997). Notice that in our context, this is an indirect effect on adoption, whereby consumers exert a pressure on the DMU to adopt the innovation. The second, direct effect on adoption comes from the communication process between DMUs. As more countries adopt the innovation, the risks and costs associated with the implementation of the new technology decrease (because better implementation methods are observed by later adopters) and thus, adoption by an individual country becomes easier (Ganesh et al. 1997). Also, countries who have already adopted the system often exert peer pressure on later adopters. As a result of all these (direct and indirect) effects, we hypothesize:[5]

[5] This hypothesis assumes that time is a good proxy (or is highly correlated) with the combined effect of an increase in the number of previous adopters and their accumulated experience (cf. Helsen and Schmittlein 1993).

H1: Elapsed time since the introduction of the innovation is positively related to a country's likelihood of adoption for countries that will ultimately adopt the innovation.

The hypothesis explicitly recognizes that some countries may never adopt an innovation, and as a result their adoption behavior is independent from other countries'.

Our next hypothesis is related to the nature and size of the "relative advantage" (Rogers 1983) or benefit that an innovation may provide for a certain country. Countries are expected to adopt a new technology when their perceived utility from the new technology exceeds their status-quo utility (Chandrashekaran and Sinha 1995). This explains why certain innovations might never be adopted by some countries. For those countries where adoption will eventually occur, its timing will be negatively related to the size of the benefit that the innovation represents. In the context of cellular telecommunications services, for example, the technology mostly suits areas where the population concentration is high, as in large cities. Hence, for these services, we expect the perceived utility of the new technology to be directly related to a country's number of major population centers. In other contexts, relevant proxies to measure "advantage" might lead to different concrete measures.

H2: The higher the relative advantage of the innovation for a country, the sooner the country adopts it.

The attractiveness of a new technology is not uniquely a function of the countries' *current* situation. Market growth, a determinant of the *future* demand for the innovation is another critical factor in the decision process. Following previous research (see e.g. Antonelli 1993), we expect earlier adoption in high-growth markets. Indeed, any delay in the adoption of the new technology causes the installed base of the old technology to become larger, which will translate in increasing substitution costs. Formally,

H3: Markets growing faster will adopt the innovation sooner.

Our next two hypotheses deal with economic/political factors. We capture two important aspects: (1) the wealth of a country, and (2) whether it has an isolated economy. Rogers (1983) notes

that innovators tend to have a higher income. In the context of international diffusion, we also expect that wealthier countries will adopt earlier, as their consumers can afford greater economic sacrifice associated with the investment in new innovations (Lee 1990). Also, as developed infrastructures reduce the cost of technology transfers (Mascarenhas 1992), the adoption of a new technology is associated with relatively smaller costs in wealthy countries. Several other authors have made similar conjectures (e.g. Antonelli 1993; Gatignon and Robertson 1985). Finally, following Mascarenhas (1992), we hypothesize that artificially isolated economies such as the centrally-planned economies of the former East-block will tend to lag in adopting innovations. While from a practical perspective this hypothesis has limited current interest (as most countries have recently switched political regime), it constitutes a straightforward test for the viability of our approach.[6] In isolated economies where citizens are restricted to travel or communicate with the outside world, cross-country communication processes between consumers and peer pressure from other countries to adopt an innovation have a smaller or even negligible effect (Putsis et. al. 1997). Thus, within the diffusion paradigm, it is natural to hypothesize that these countries will adopt later. An additional reason contributing to the late adoption of these countries might be the lack of economic incentives to innovate (Amann and Cooper 1982; Leary and Thornton 1989). In summary, based on previous theoretical research on the effect of economic and political factors on diffusion, we formalize the following hypotheses:

H4: Wealthier countries adopt the innovation earlier.

H5: Isolated economies tend to adopt innovations later.

The third general exogenous factor we consider is the countries' social structure. It is a well-known result that innovations diffuse slower in heterogeneous social systems, as interpersonal influence processes are less effective (Gatignon and Robertson 1985). We extend this hypothesis, and conjecture that countries with heterogeneous social systems also tend to try a new innovation later. This is because a heterogeneous social system is less effective in exerting pressure on the DMU of the country. Furthermore, as we argued, for the adoption of most technological innovations, social consensus has to be reached on regulations and standards before the actual product is commercially

[6] Beyond being of theoretical interest, whether a country's economy is isolated or not from the rest of the world economy also serves as an important control variable when estimating the impact of the other covariates.

available. We argue that a heterogeneous social system in which communication is less efficient (and, as a result, consensus is harder to reach) is less likely to innovate (see also Robertson and Wind 1980). Formally:

H6: A country's adoption timing is negatively related to its society's heterogeneity.

Our first hypothesis already captures the idea of a communication process and peer pressure between countries. Gatignon and Robertson (1985, p. 858) conjecture, however, that cross-country communication and peer pressure is not homogeneous across countries (see also Putsis. et. al. 1997). A similar argumentation is used by Vernon (1979) to support the continued existence of international product life cycles. Some countries, namely those having economic, social and/or cultural similarities are likely to have more influence on each other, as they interact more frequently. Also, countries with similar macroeconomic environments are assumed to have similar operational contexts and administrative procedures (Craig et al. 1992, p. 776).[7] Some of this similarity has been captured by Hypotheses 2-6. Clearly, there are additional similarities in social, cultural and economic factors that are hard to capture with a single construct. The following hypothesis summarizes the *incremental* effect of these factors.

H7: The higher the proportion of similar countries having adopted the innovation, the higher the probability that a country will also adopt the innovation.

As mentioned earlier, the above hypotheses represent a general translation of the diffusion paradigm to the breadth dimension of the global diffusion process. A rigorous test of these hypotheses in a particular product context requires the restatement of the hypotheses taking into account the specific operationalization of the constructs and the availability of appropriate data. It also requires statistical procedures to rigorously test the hypotheses. Such a procedure is presented in the next section.

[7] One might argue that cross-country influence is also related to geographic proximity. However, in the information age, geographic proximity is relatively less important than socio-cultural and political/economic proximity.

3. MODEL DEVELOPMENT

One of the reasons for studying the breadth dimension of global diffusion separately from its depth dimension is that most often, researchers can collect dis-aggregate data on the former, i.e. it is known which country adopted the innovation at what point in time. Micro-level adoption models are well-suited to test research hypotheses in this setting. Beyond allowing the probability of adoption to be heterogeneous across countries (Chatterjee and Eliashberg 1990; Sinha and Chandrashekaran 1992), these models can also incorporate various causal factors which may affect the individual adoption decision. Building on this research philosophy, we apply the flexible split-hazard specification developed in Dekimpe et al. (1997) and Van de Gucht and Moore (1997), which has the following properties:[8]

Information on both completed and censored observations is taken into account: The duration of interest (T) is the number of periods (e.g. months) elapsed since the innovation first became available and, respectively, the time of a country's adoption (for the completed observations) or the end of the observation period (for the so-called censored observations). Parameter estimates for the factors influencing this duration are obtained through maximum-likelihood estimation, and all countries, irrespective of whether or not they have adopted (tried) the innovation by the end of the observation period, are contributing to the likelihood function.

A correction is made for the grouped nature of the data: Oftentimes, the correct day of adoption is not known for every country. Instead, information is typically available on the *discrete time interval* within which the adoption took place (e.g. the month or quarter). In the specification of the likelihood function, we correct for the discrete nature of the data, as a failure to do so has been shown to result in inconsistent parameter estimates, with increasing asymptotic bias as the grouping interval becomes more coarse (Kiefer 1988).

Both fixed and time-varying covariates can be incorporated: To test the hypotheses developed in Section 2, covariates need to be incorporated into the model. Some of these covariates are fixed (e.g. its society's heterogeneity – H6), while others are clearly time-varying (e.g. the proportion of similar countries that have adopted – H7). The adopted specification is flexible enough to incorporate both sets

[8] A more detailed discussion on how these different properties are reflected in Equations (1) and (2) is available from the authors upon request.

of covariates, provided the time-varying covariates remain constant within each discrete time interval (e.g. a month or quarter), but can change from interval to interval.

The baseline hazard is estimated non-parametrically: A variety of distributional forms have been used in the literature to describe the nature of the time dependence in the adoption process, such as the exponential (Hannan and McDowell 1984), Weibull (Chandrashekaran and Sinha 1995), Gompertz (Dixon 1980) and log-normal (Sinha and Chandrashekaran 1992) distribution. However, few a priori reasons exist to prefer any particular specification (see e.g. Levin et al. 1987 or Trajtenberg and Yizhaki 1989 for an elaborate discussion). Moreover, the selection of an incorrect parametric form has been shown to result in inconsistent parameter estimates (Meyer 1990). We therefore adopt the non-parametric approach advocated in Vanhuele et al. (1995), which basically consists of a piece-wise approximation to an underlying, possibly very complex, continuous time-dependence pattern. Its main advantage lies in the fact that it results in consistent parameter estimates, even when the latter pattern is unknown. However, some of the aforementioned parametric specifications will also be implemented to validate our substantive findings.

A correction is made for unobserved heterogeneity: Often, and especially when working in a global setting, it is impossible to incorporate *all* factors that can have an impact on a country's adoption timing. Some factors may be hard to quantify (e.g. the attitude of the country's political leaders towards new technologies) or may not be available in the data set at hand (in our data set, for example, no information was available on the number of countries forming the government at any given point in time; cf. infra). Not accounting for these omitted factors (often referred to as unobserved heterogeneity) has been shown to result in inconsistent parameter estimates for the included covariates, and to cause a negative duration dependence (which could invalidate our inferences for H1). Our model specification will therefore incorporate a correction for unobserved heterogeneity, and will do so through the gamma mixing distribution (see Vanhuele et al. 1995 for an elaborate motivation of this choice).

Combining the above properties, the following expression for the log-likelihood function is obtained (we refer to Dekimpe et al. 1997 or Vanhuele et al. 1995 for the mathematical derivations):

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

where

d_i = an indicator variable taking the value of one when the observation is censored, and zero otherwise;

a, r = parameters of the gamma mixing distribution, with mean r/a and coefficient of variation $r^{-1/2}$;

$X_i(t_i)$ = a set of (fixed and/or time-varying) covariates;

$D_i(t_i)$ = a set of time-varying dummy variables used for the piece-wise approximation of the underlying time-dependence pattern;

β, c = parameter estimates capturing, respectively, the impact of the included covariates and the nature of the time dependence; and

$B_i(t_i\text{-}1) = \Sigma_j \exp[\beta X_i(j) + c\, D_i(j)]$ $(j=1, \ldots, t_i\text{-}1)$.

The assumption that eventually every country will adopt is relaxed: To explicitly allow for the fact that some countries may never adopt the innovation (not even as t $\rightarrow\infty$), we extend the model in Equation (1) using the (homogenous) split-hazard approach of Dekimpe et al. (1997). Intuitively, this approach allows for the existence of two (latent) sub-populations, one which will eventually adopt and one which will not. The hazard specification developed in Equation (1) *only applies to the former sub-population.*[9] Using the same terminology as before and defining $\delta\,(0 \leq \delta \leq 1)$ as the size (proportion) of the sub-population of eventual adopters, the log-likelihood function becomes (see Van de Gucht et al. 1997 for technical derivations):

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

[9] This allows us to rigorously test hypothesis 1, which states that the time since introduction is positively related to a country's likelihood of adoption *for countries that will ultimately adopt the innovation.*

4. EMPIRICAL STUDY: GLOBAL DIFFUSION OF CELLULAR SERVICES

4.1 Operationalization of variables

As argued before, in any particular application, hypotheses 1-7 need to be refined taking into account the specific product context and data availability. In what follows, we will discuss how the general constructs in section 2 are operationalized in the context of cellular services, and their impact on our hypotheses.

Within our modeling framework, there is no need to introduce a specific variable to test **H1**. The time-dependent "contagion effect" is naturally captured by the model's baseline hazard which according to the hypothesis is expected to increase over time (Helsen and Schmittlein 1993). Remember, however, that only countries which will eventually adopt are affected by this demonstration effect. Our modeling framework provides a natural test to compute the proportion of countries that will eventually try the innovation. Indeed, equation (2) describes a split-hazard specification where the population is assumed to consist of two subgroups: one that will eventually adopt the innovation (δ), and another that will never do so ($1 - \delta$). We did not find any theoretical reasons why cellular services would not provide any benefits to a country's consumers. We also conducted in-depth interviews with managers and based on their opinions, we hypothesize that eventually all countries will adopt the cellular technology. This conjecture might only reflect wishful thinking by managers, though. Mascarenhas (1992), for example, argues that international diffusion is often incomplete. Formally, **H1** is extended with the hypothesis that eventually, all the countries of the world will adopt cellular technology, and hence, the baseline hazard estimated in **H1** will apply to all of them. In our modeling framework, we test this hypothesis by showing that the size of the group of countries that will never adopt the innovation is not significantly different from zero.

In contrast with **H1, H2** needs to be adjusted to the product context. While several factors may contribute to the relative advantage of cellular services, the one that is clearly relevant and measurable across all countries of the world is the level of urbanization. We used the number of major population centers to measure this variable and hypothesize that everything else being equal, the higher the number of major population centers in a country, the sooner it will adopt cellular services. **H3** states that the expected time till adoption is negatively related to the market's growth rate. We simply use population growth rate to operationalize this variable. This proxy was chosen as a country's population size is directly related to the market potential for this product category, and

since population growth rate is a globally available variable. To measure a country's wealth (**H4**), we use GNP per capita, which is broadly used in international research (see e.g. Helsen et al. 1993).[10] We hypothesize that the higher a country's GNP/capita the sooner it will adopt an innovation (cf. Lee 1990). To test **H5**, former East-bloc countries and other communist countries like Albania and North Korea were chosen as the set of isolated economies and they were simply captured with a dummy variable. Considering the constraint that we need to find a globally-available proxy to capture each country's social heterogeneity (**H6**), we have chosen to operationalize the construct through the number of ethnic groups in the country's society. Thus, we expect that countries representing a large number of ethnic groups, which very often also represent different languages, religions and/or cultures, will tend to adopt an innovation later. To capture the concept of social similarity beyond that described by the above variables (**H7**), we grouped countries in nine clusters established by the World Bank based on social/cultural, economic and political dispositions (see Craig et al. 1992 for a review of similar clustering procedures). We conjecture that everything else equal, a country is more likely to adopt cellular systems sooner if a larger proportion of its World Bank group has already adopted such systems.[11]

4.2 The data

For the purpose of our empirical study, a comprehensive data set was built using a number of different sources. Data on cross-country adoption timing (the dependent variable) in the cellular telephone industry were collected from the relevant government agencies, trade associations, and the International Telecommunications Union, a United Nations Agency. The innovation is defined as "mobile cellular-like telecommunications subscriptions" (as opposed to a particular type of terminal equipment). We had information on the date the technology first became available for 184 countries. Here, adoption is considered to have started when a country first commercially launched the cellular network and had its first paid subscriber. While a number of alternative starting times might be

[10] We have also used another measure (control variable), the death rate of a country, which intends to measure the opposite of wealth: poverty. Since income distributions are typically very skewed, this additional variable (which interestingly, is little correlated with GNP/capita) helps us to better capture the concept of a country's wealth. In particular, it helps to capture the idea that countries where wealth belongs to a very small sub-population typically have little infrastructure, and are socially divided, meaning that coordination is harder to reach. As a result, everything else being equal, in countries where death rates are higher, adoption is expected to occur later.

[11] It should be noted that we do not allow for further asymmetric influences within each World-Bank group. Country-specific influences (capturing communication between country i and country j) are allowed in the mixing framework of Putsis et. al. (1997), but the resulting procedure becomes too unwieldy when many countries are considered.

considered (e.g. the time when the political decision was made to create a network, or the time when the construction started on the first cell), these alternatives are largely unobserved, can be ambiguous from one country to another, and do not reflect a market outcome (e.g. the time when commercial operations began).

Cellular technology was first tried on a limited scale by the government of Qatar in June 1979, which became the starting point of the time axes. Japan then introduced the technology by the end of 1979, and was therefore given a duration of seven (i.e. the first commercial application appeared in the seventh month the technology was available), while France adopted in November 1985, i.e. after 78 months.[12] For countries which had not yet adopted cellular technology by September 1990 (the censored observations), a duration of 136 was recorded. September 1990 was used as the end of the observation period, since it enabled us to clearly distinguish East-bloc countries, a distinction which became blurred after the fall of the Berlin Wall. Going beyond September 1990 would also have affected the sample size in that the national boundaries of a number of countries changed afterwards. This duration was obtained for 184 countries, located in Africa (55 countries), Asia (37 countries), Europe (32 countries), the Americas (45 countries) and other regions (15, mostly island, countries). The geographical coverage of the data set therefore exceeds considerably that of most international-business studies (see e.g. Thomas et al. 1994), and specifically, of most international-diffusion studies (see Dekimpe et al. 1997 for an overview).

The data covering the covariates were collected from Euromonitor Ltd. and the *World Factbook* (Central Intelligence Agency, 1993). As data on 184 countries are difficult to collect on a year-to-year basis and since the cross-country variation of the variables is orders of magnitude higher than the within-country variations during the observation window, we treat the exogenous covariates as time-invariant, i.e. we assume that they do not vary in a systematic fashion over the considered time span.

The highest correlation between the respective independent variables does not exceed 0.4, suggesting that multicollinearity is not a problem. Also, this low correlation between the variables shows that GNP/capita, crude death rate and the "East-bloc" dummy variable capture fundamentally different economic/political dimensions, and as such need to be entered in the model separately.

[12] For 87% of the adopting countries, we knew both the year and month of adoption so that we could calculate unambiguously the associated grouping interval. For 13% of the adopting countries, only the year of adoption was known, and for those countries, we assumed adoption occurred in the middle of the year (June). None of our

Finally, to measure how many nations in a country's "World-Bank group" have adopted cellular technology, we have re-calculated this variable for each month in the observation window. This resulted in a time-varying endogenous covariate. 156 countries fit into one of the World-Bank categories. Rather than combining the remaining 28 countries in an "others" category (which would imply considering Cuba and Monaco as similar countries), we tested the impact of this endogenous factor on the more restricted data set of 156 countries.

4.3 Estimation and hypothesis testing

Parameter estimates for a number of different model specifications are given in Table 1. In Table 1, we impose the managerial assumption that all countries will eventually adopt; i.e. parameter estimates are derived from Equation (1). This assumption is tested later on. The first column of Table 1 presents the estimates for a model which does not yet include the time-varying proportion of earlier adoptions in a country's World-Bank group. With respect to the exogenous covariates, it is found that non East-bloc countries, with a high GNP per capita, few ethnic groups and many major population centers tend to be early adopters of cellular technology. Thus, **H2, H4, H5** and **H6** are supported by the data.[13] Population growth (a surrogate for the need to expand the telecommunications infrastructure - **H3**), on the other hand, had no significant impact on the countries' adoption timing in this model specification.[14]

The increasing baseline hazard supports the notion of a "demonstration" (Mansfield 1968) or "snowball" (Helsen and Schmittlein 1993) effect (**H1**) resulting from previous adoptions within *and* outside a country's World-Bank group: as more countries have adopted the technology, the uncertainty surrounding its value diminishes since potential adopters can benefit from the experience of the earlier adopters.[15] We illustrate the resulting positive time dependence in Figure 2, which depicts the evolution of the hazard rate for an "average" non East-bloc country.

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substantive results was affected, however, when we assumed that adoption occurred at the beginning or end of the year.

[13] Also, the poverty proxy had a significant impact, which provides empirical support for its inclusion as a control variable (cf footnote 10).

[14] Similar conclusions (in sign and order of magnitude) were obtained for all hypotheses when working with a parametric (quadratic and Weibull) specification of the baseline hazard (detailed results are available from the authors upon request).

[15] For the sake of parsimony we restricted the number of discrete jumps in the baseline hazard to one every three years. Our substantive results were not affected by this choice however, as similar results were obtained when working with shifts after 2 or 4 years. Moreover, similar conclusions with respect to the increasing nature of the

To obtain further insights into the relative importance of the demonstration effect, we explicitly account for the proportion of previous, *similar* adopters in Model 3. As indicated before, the World-bank classification which is used as a measure of similarity is only available for 156 countries. To enhance the comparability with the previous models, we re-estimated Model 1 on this restricted sample (see Model 2 in Table 1), and found the results to be very similar across the two samples. One difference appears in the initial base hazard (r/a) which becomes larger when estimated on 156 countries. Some face validity for this result is obtained when noting that only 7 of the omitted countries had adopted the technology, and that those seven all did so shortly before the end of the observation period. Put differently, they appear to have been "lagging" in their adoption decision, and their omission from the sample caused an increase in the average hazard for the remaining countries. Consistent with the hypothesis that there is a strong demonstration effect among "similar" countries (H7), a significant positive parameter estimate is obtained in Model 3. In terms of the economic significance of the estimate, a country's hazard in any given year is 34 (80) percent higher when one fourth (half) of the countries in its World-Bank group have adopted the technology than if none had done so. Also, the baseline hazard in Model 3 only reflects the demonstration effect by non-member countries, and is not as steep as in Model 2.[16]

As indicated before, the demonstration effects reported in Table 1 only apply to countries which will eventually adopt, and in the specification/estimation of Equation (1), we imposed the managerial intuition that eventually all countries will do so. To empirically test this assumption, we estimated the split-hazard model of Equation (2). The parameter estimate for the proportion of ultimate adopters (the parameter δ) converged to one, and the *same* parameter estimates as in Model 3 of Table 1 were obtained. As such, in the long run, all countries are indeed expected to adopt cellular-telephone networks.[17]

To get some further insights into the relative magnitude of the different effects, we compute in Table 2 the point elasticities, given by $\beta_i X_i$. Following Gupta (1991), we report the elasticities evaluated

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baseline hazard were found in a variety of competing parametric specifications for the baseline hazard, namely for the Gompertz, quadratic and Weibull distribution.

[16] Comparable findings were obtained when working with a parametric specification of the baseline hazard, with estimates for the demonstration effect of similar countries ranging between 1.15 (quadratic) and 1.35 (Weibull), compared to 1.18 for the non-parametric specification.

[17] To further validate this substantive result, we estimated a model with a quadratic baseline specification, and checked whether the quadratic term was negative and significant (in which case the hazard rate would converge to zero, and the survival function would stabilize at a non-zero level; see e.g. Helsen and Schmittlein 1993). This was not the case, as the quadratic-trend term was, while negative, far from significant ($\chi^2(1) = 0.52, p > 0.4$).

at the sample mean for the fixed exogenous covariates (**H2-H6**), and at a number of relevant proportions (25, 50 and 75%) for the time-varying endogenous variable (**H7**). The number of major population centers, which is a main determinant of the innovation's perceived utility or relative advantage as compared to existing alternatives, emerges as the most important driver of the countries' speed of adoption. The GNP per capita variable, on the other hand, which had been found to be a major determinant of the speed of *within-country* diffusion (see e.g. Helsen et al. 1993) comes out as having less explanatory power to segment countries on the breadth dimension.

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

5. CONCLUDING REMARKS

5.1. Pragmatic considerations and limitations

This paper studies the global adoption process, or the timing of initial adoption of an innovation at the country level (breadth). In addition to extending the diffusion paradigm to a context where the adopting unit is a country, our approach allows researchers to rigorously test a number of hypotheses/theories, whether generated by the academic community, managers, or economic planners. There are, however, a number of pragmatic issues associated with generating and testing international theories of diffusion which should be kept in mind. First, while we developed a general framework of international adoption, the operationalization of the hypotheses remains, to some extent, category specific. For example, in our empirical study, population concentration proved to be the most important predictor of a country's adoption timing. Clearly, this variable is crucial in the context of mobile telecommunications but may be a less appropriate operationalization of the relative-advantage concept in other settings. As such, we do not claim that the covariates included in our study are equally relevant

for all other innovations. Thus, our empirical results should be interpreted as only the first, yet rigorous, step towards the development of empirical generalizations in the area of global adoption sequencing.

Second, a practical problem in testing "global theories" is the need to use globally representative proxies. As applied international researchers are well aware, the requirement to use covariates which measure international differences across 184 countries leaves us with a limited set of variables (e.g. basic socioeconomic characteristics). As a consequence, some of the factors which could potentially have an impact on the adoption timing were not included in the model because their values were only available for a small fraction of the countries, and also the development of multi-item scales was unfeasible (see Singh 1995 for a detailed discussion on measurement problems in international research), which made a correction for unobserved heterogeneity an important property of our hazard specification.

5.2 Managerial implications

For decades, marketers have used the diffusion paradigm, extended from Rogers (1983), in order to classify customer groups into temporal segments: from innovators and early adopters, to laggards. This paradigm is useful as it focuses attention on the fact that not all consumers are alike, and that earlier adopters, in particular, may have fundamentally different profiles than later adopters. Armed with this knowledge, marketing strategies become dynamic over time to optimally design, price and distribute products. This study is the first, to our knowledge, to extend this paradigm to the community of nations. Limited in resources, especially for new products or technologies, managers playing the "global game" must prioritize countries by creating temporal segments equivalent in nature to those characterized by Rogers. Which countries are likely to adopt earliest and become the opinion leaders for other, especially similar, countries? This research suggests a few rules of thumb which merit further empirical testing. Our profile of the innovative country is one that is wealthy (on a per capita basis), has a highly concentrated population, is open (part of the global economy) and is culturally homogeneous. Laggard countries have an opposite profile. Who will follow the innovators in adoption timing? These will be "similar" to the earlier adopters, but less wealthy, less culturally homogenous, etc. As time passes and a greater proportion of "similar" countries adopt, the more pressure on the later adopters to also implement the technology. This rule of thumb clearly runs against the notion of immediately launching a product on a global basis. Rather, it gives strong support for the idea that

products diffuse internationally, and that countries can be segmented based on their likely adoption timing.

5.3. Extensions

While the modeling approach suggested is quite general, we have illustrated it on an industry undergoing a *decentralized* process. Indeed, the manufacturers themselves did not determine when sales would begin in a specific country. Instead, local governments determined from what point in time the technology was allowed to be introduced in their country. Such processes are likely to exist for a wide variety of technologies or products such as most medical products, telecommunication services, energy-supply systems, electronic products which must meet local type approval, cosmetics, or any other packaged consumer goods which require government approval or face non-tariff barriers. While we recognized the particular nature of the decision making unit under such scenarios, it would be interesting to investigate in more detail the decision process itself for decentralized diffusion processes.

For other industries, global cross-country diffusion may be the result of what Rogers (1983) calls a *centralized* process whereby the firm (i.e. the change agent) systematically determines where the technology should be sold next. When firms themselves plan the introduction sequence (i.e. when dealing with centralized processes), one can still use the proposed modeling techniques as research tools, though the nature of the explanatory variables may be somewhat different. Clearly, the use of the proposed modeling approach should be extended to such processes.

Finally, we have applied the model to a typical "high technology" industry/service. Future research is warranted on generating empirical generalizations with respect to cross-country adoption patterns. Do most categories undergo international diffusion patterns? Are the "innovative" countries similar across categories (similarly for the other categories of adopters identified by Rogers)? If there is variance across categories, what factors explain these differences? In particular, as the discussion above suggested, our research has lead to profiles of typical innovators (rich, culturally homogeneous, concentrated, free-market economies) versus laggards (impoverished, culturally heterogeneous, dispersed populations). While this profile might intuitively be applicable to most consumer goods and high technology categories, the leap may be hazardous. Given that methodologies have now been presented to address this issue, we believe that greater efforts should be spent on empirical research to test the generalizability of our findings.

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Table 1. Parameter estimates for the cross-country timing model

	Model 1	Model 2	Model 3
r/a	0.0002	0.0006	0.0009
Time Dependence (H1)			
c_2 (4-6 yrs)	1.130**	0.741*	0.517
c_3 (7-9 yrs)	2.988**	2.461**	2.008**
c_4 (10-12 yrs)	4.297**	3.543**	3.019**
Exogenous Factors			
Demographic Factors			
No. of Major Population Centers **(H2)**	0.267**	0.194**	0.178**
Avg. Annual Pop. Growth Rate **(H3)**	-0.088	-0.237	-0.235
Economic Factors			
GNP per Capita ($10,000) **(H4)**	1.239**	1.131**	0.942**
Former East-Bloc **(H5)**	-2.834**	-2.541**	-2.253**
Social System Factors			
No. of Ethnic Groups **(H6)**	-0.206**	-0.201**	-0.193**
Endogenous Factors			
Proportion of World Bank Group **(H7)**	-	-	1.175**
N	184	156	156
Log-likelihood	-363.63	-305.70	-304.35
AIC [(-2LL) +2(# parms)]	749.26	633.40	632.70

*: $p < 0.1$; **: $p < 0.05$ (one-sided tests)

Model 1: 184 countries – only exogenous covariates
Model 2: 156 countries – only exogenous covariates
Model 3: 156 countries – exogenous and endogenous covariates

Table 2. Adoption Rate Elasticities (*)

	Model 1 (N = 184)	Model 3 (N = 156)
Exogenous Factors		
Demographics Factors		
No. of Major Population Centers (**H2**)	2.136	1.636
Avg. Annual Pop. Growth Rate (**H3**)	n.s.	n.s.
Economic Factors		
GNP per Capita (**H4**)	0.628	0.420
Former East-Bloc (**H5**)	-0.283	-0.248
Social System Factors		
No. of Ethnic Groups (**H6**)	-1.03	-0.998
Endogenous Factors		
Proportion of World Bank Group (**H7**)		
25%	-	0.294
50%	-	0.588
75%	-	0.881

(*) Evaluated at the sample mean for the exogenous variables; n.s. = not significant.

Figure 1. Worldwide Adoptions of Cellular Subscriptions

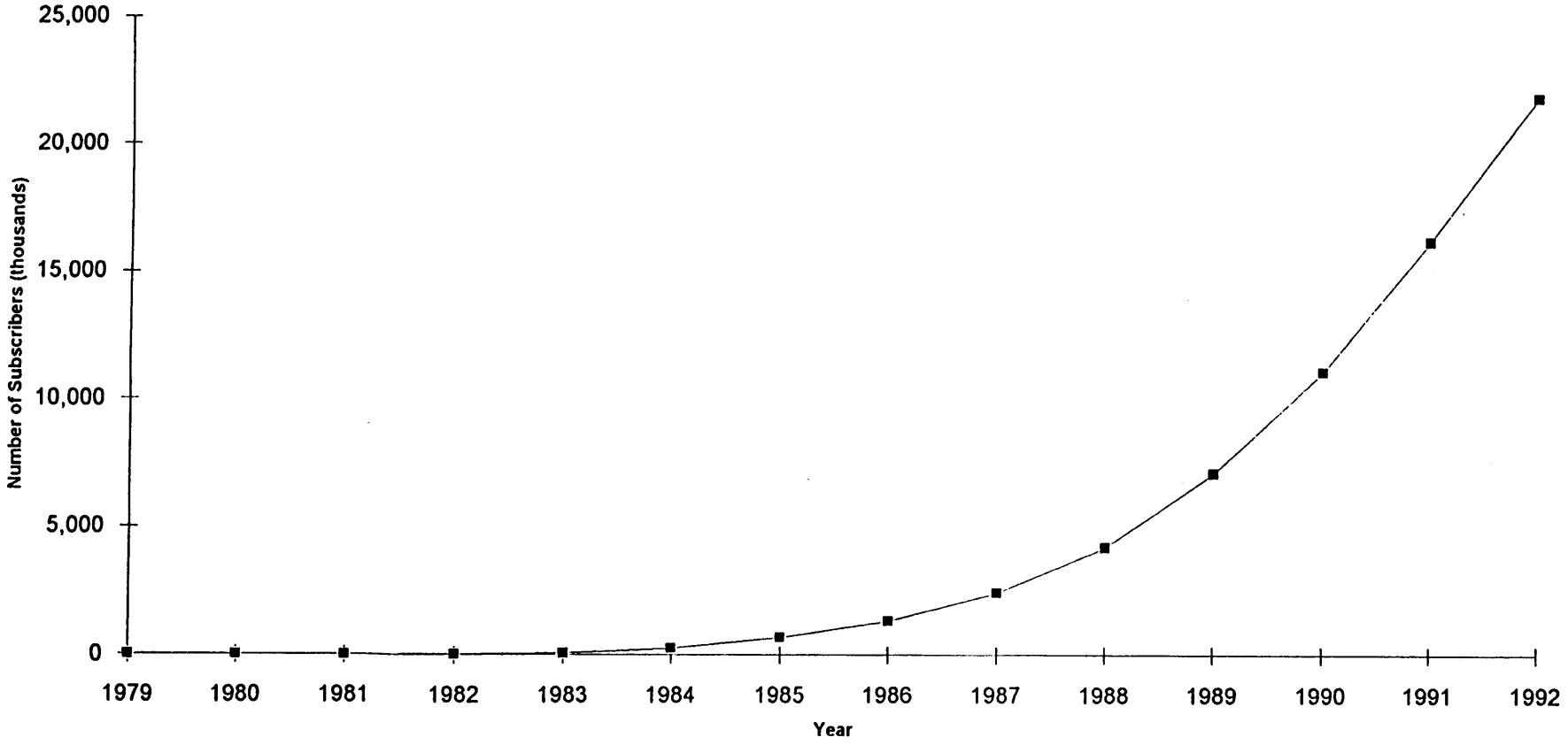
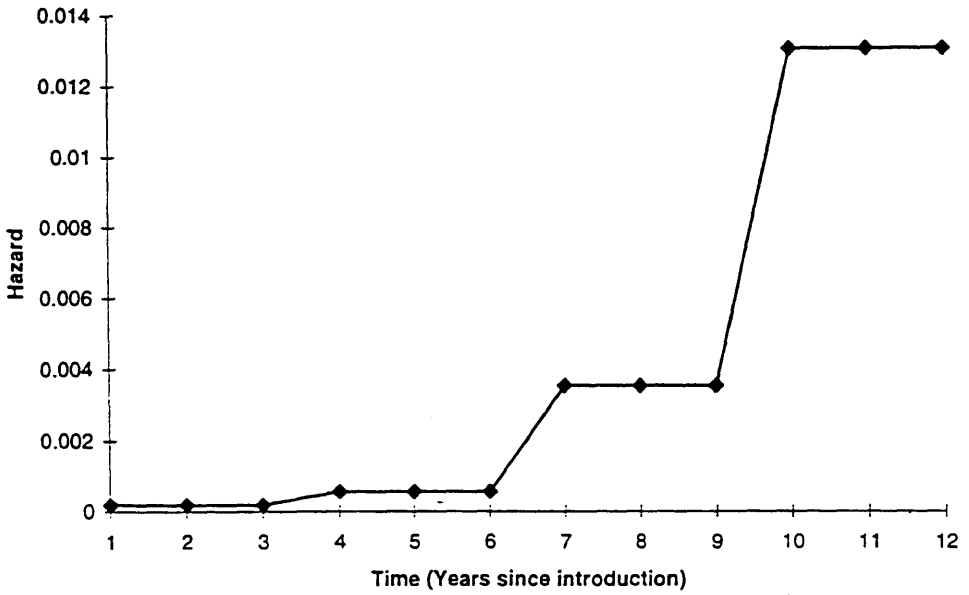


Figure 2. Evolution of the Hazard Rate



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

APPENDIX TO "GLOBALIZATION": MODELING TECHNOLOGY ADOPTION TIMING ACROSS COUNTRIES

(available from the authors upon request)

To explain the variability in the adoption timing of an innovation, and test the hypotheses developed in Section 2 of the paper, a flexible hazard model is proposed. For ease of exposition, we develop the final model specification in three stages. In Stage 1, a flexible hazard model is developed which incorporates both fixed and time-varying covariates. To obtain insights into the nature of the time dependence (used as a proxy for the contagion effect), a non-parametric specification of the baseline hazard is introduced. Inferences about the time dependence are biased downwards, however, when no correction is made for unobserved heterogeneity. We therefore extend the model in Stage 2 to explicitly account for the fact that we will be unable to capture *all* potentially relevant factors. Finally, in Stage 3, we consider two alternative approaches to test the managerial intuition that every country will eventually adopt the new technology: a split-population extension of the model presented in Stage 2, and the use of a deficient parametric distribution for the baseline hazard.

1. Regular (non-split) hazard model without correction for unobserved heterogeneity

Let T denote the random duration until a country adopts the technology with probability density function $f(t)$, cumulative distribution function $F(t)$ and hazard function $\lambda(t)$. Discrete grouping intervals $[t_{k-1}, t_k)$, $k = 1, 2, ..., m+1$, $t_0 = 0$ and $t_{m+1} = \infty$ are defined, and adoption in duration interval $[t_{k-1}, t_k)$ is recorded as t_k. It should be emphasized that t_k does not refer to actual calendar time, but to the number of discrete time intervals (in our case, months) elapsed since the innovation first became available.

Parameter estimates are obtained through maximum-likelihood estimation, and the contribution to the likelihood function differs depending on whether or not a country has adopted the innovation by the end of the observation period. The contribution to the likelihood function of country k which adopted the technology in month t_k is given by $S(t_k\text{-}1)\text{-}S(t_k)$, where the survivor function $S(t_k) = 1\text{-}F(t_k)$ denotes the probability that the country has not yet adopted the new technology after t_k months. By working with the difference of survivor functions rather than with the density function, we recognize the discrete nature of the monthly duration intervals (Kiefer 1988). For country l which has not yet adopted the innovation by the end of the observation period, the contribution to the likelihood function

is given by $S(t_i\text{-}1)$, i.e. we assume that censoring takes place at the beginning of the duration interval. The contribution to the likelihood function of any country i can therefore be written as:

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

where d_i is an indicator variable which takes the value of one if the country has not yet adopted by the end of the observation period.

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

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

This expression consists of three building blocks. First, λ_0 gives the adoption rate of countries in the base group in the first month after the technology's introduction. The base group is defined as those countries for which all covariates, given by the vector $X_i(t)$, are zero. Second, when some of the covariates are different from zero, the country's hazard is multiplied by $\exp[\beta X_i(t)]$. A positive β coefficient implies that an increase in the value of the associated covariate augments the (conditional) adoption probability, or conversely, reduces the expected time until adoption. Finally, a set of time-varying dummy variables $D_i(t)$ is added to capture a wide variety of time dependencies. Consider, for example, the situation where a separate dummy is included for every possible adoption month. The time-varying dummy associated with month three is always zero, except during the third month after the technology became available, when it takes the value of one, i.e. its different values are (0 0 1 0 ...). To avoid identification problems when simultaneously estimating c_1 and λ_0, no dummy variable should be included for the first month. 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 month.

This approach makes no distributional assumption with respect to the nature of the time dependence, and is therefore called non-parametric (Dekimpe and Degraeve 1997; Vanhuele et al. 1995). The only assumption made is that within a grouping interval (e.g. a month) the hazard remains constant. Intuitively, this is equivalent to a piece-wise approximation of an underlying, possibly very

complex, continuous time-dependence pattern. Its main advantage is that it results in consistent parameter estimates even when the true form of the baseline is unknown. In contrast, an incorrect parametric specification results in inconsistent parameter estimates (Meyer 1990). In many empirical applications, one may want to limit the number of discrete jumps in the baseline hazard, which can easily be implemented by imposing restrictions on some of the *c*-parameters. Rather than allowing for a different *c*-parameter in every month, we allow in our application for a discrete shift after every three years.

Obviously, if the correct parametric form of the underlying duration distribution could be selected, a more parsimonious specification might result. However, little is known about the appropriate functional form to describe the adoption process of technological innovations (Levin et al. 1987, p. 13; Trajtenberg and Yizhaki 1989, p. 36), which has resulted in a multitude of distributional forms in previous research, such as the exponential (Hannan and McDowell 1984), Weibull (Chandrashekaran and Sinha 1995), Gompertz (Dixon 1980) and log-normal (Sinha and Chandrashekaran 1992) distribution. Given the absence of compelling a priori reasons to select any particular specification, and the inconsistency of the parameter estimates when an incorrect form would be selected, we opt for the more flexible non-parametric specification. However, we use various of the aforementioned parametric specifications to validate our substantive findings.

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

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

When the time-varying covariates (e.g. the proportion of previous adopters) are assumed to remain constant within a given month, but are allowed to vary from month to month, (3) can be written as (Dekimpe and Degraeve 1997; Gupta 1991):

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

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

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

2. Accounting for unobserved heterogeneity

In Equation (5), we basically assume that every country in the base group has the same initial adoption probability λ_0. However, some of the factors that can have an impact on a country's adoption timing may be hard to quantify (e.g. the attitude of its political leaders towards new technologies), or may not be available in the data set at hand (e.g. in the data set used in our empirical application, we did not have detailed information on the number of political parties forming the government at any given point in time). Not accounting for these omitted factors (often referred to as unobserved heterogeneity) has been shown to result in inconsistent parameter estimates for the included covariates and to cause a spurious negative duration dependence, as reflected in a downward bias on the *c*-coefficients (see e.g. Lancaster 1990). The latter phenomenon could invalidate our conclusions about the nature of the contagion effect, and we therefore extend the model in equation (5) with a correction for unobserved heterogeneity. Following Gupta (1991) and Vanhuele et al. (1995), we 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 closed-form solution for the likelihood function given in Equation (6) (see Vanhuele et al. 1995 for a formal proof):

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

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 earlier models.

3. Relaxing the assumption that eventually every country will adopt

Finally, two approaches are adopted to explicitly allow for the fact that some countries may never adopt the innovation. First, we extend the model in Equation (6) using the homogenous split-hazard approach of Sinha and Chandrashekaran (1992). Intuitively, this approach allows for a discrete spike at $\lambda_0 = 0$. The magnitude of this spike allows us to discriminate between the managerial intuition that in the long run all countries will adopt the technology (spike of magnitude zero), and Mascarenhas' (1992) contention that international diffusion is often incomplete (spike of non-zero magnitude). Following Sinha and Chandrashekaran (1992), an indicator variable A_i is defined, where A_i is equal to

one if the country belongs to the group of eventual adopters, and zero otherwise. If the probability of $A_i=1$ (denoted as δ_i) is assumed to be homogeneous across all countries (i.e. $\delta_i=\delta$), it can be interpreted as the fraction of countries that will adopt in the long run. A likelihood-ratio test can subsequently be used to test whether δ is equal to one.

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

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

If all countries which will eventually adopt have the same λ_0, one can substitute equation (4) into (7) to derive a split-hazard model which does not yet correct for unobserved heterogeneity among the eventual adopters. In order to account for this heterogeneity, one can again let λ_0 be distributed according to a gamma mixing distribution. After lengthy derivations, the following expression for the log-likelihood function is obtained (Dekimpe et al. 1997; Van de Gucht and Moore 1997):

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

An alternative way to allow for the possibility that adoption will never take place for some countries is to work with a degenerate (deficient) parametric density function, where $\lim_{t\to\infty} S(t)>0$ (see Lancaster 1990). Following Helsen and Schmittlein (1993), we estimate the model with a quadratic baseline hazard [i.e. $\lambda_i(t) = \lambda_0 \exp\{\gamma_1*(t-1) + \gamma_2*(t^2 - 1)/2\} \exp\{\beta X_i(t)\}$] which becomes deficient when the quadratic term (γ_2) is negative and significant. This completes the model description.

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