ABSTRACT

International diffusion of wireless telecommunication and mobile e-commerce has increased since the height of the Internet economy. However, there are a number of different issues related to the role that technology standards play in promoting diffusion. We propose a new state-based theory of technology diffusion to enable managers and policy makers to better understand the states of digital wireless phone diffusion and the factors that affect their diffusion rates, focusing on the issue of digital wireless standards. We use a modified Bass model and a coupled-hazard survival model to test a set of hypotheses that evaluate the effects of country environmental factors, digital and analog wireless phone industry environmental factors, and technology policy factors on the speed of diffusion. The results show that multiple standards and higher service prices slow down the digital wireless phone diffusion process from when it is introduced up to the time of its partial diffusion, based on an empirical operationalization of these points in time. Competition in both the analog and digital wireless phone industries also shapes the growth of diffusion. In addition, business practices and regulatory policies have short-term and long-term influences on diffusion speed.

KEYWORDS: Bass model, diffusion, digital wireless phones, empirical research, hazard model, state-based theory of technology diffusion, survival analysis, technology adoption.

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INTRODUCTION

The pressures of global competition have prompted governments of developed and developing countries to explore the means to use emerging networking technologies to achieve economic and social benefits. Evidence from country policy reports in the past decade has shown that many countries have embraced the new opportunities offered by the Internet and e-commerce (Analysys 2000). However, attention has increasingly focused on digital wireless phone technologies. Recent predictions suggest that more than two billion people will be linked by wireless communications devices by the end of 2005 (Kirkman et al. 2001). Digital wireless phone technologies have great potential for the developed and developing world, giving the latter the chance to bypass fixed network solutions that involve high maintenance costs, low reliability, and long installation delays. Similarly, developed nations can utilize this technology to improve social welfare.

Nevertheless, technology diffusion poses some challenges. For example, regulatory agencies are concerned about appropriate policies or market interventions to get diffusion going, but they are also equally interested in the appropriate timing of their actions. Simultaneously, senior managers need to know how to forecast the speed of diffusion over time. Unfortunately, prior diffusion research does little to address their concerns. This is because most diffusion research has focused on examining variables that affect the entire diffusion process (e.g., Gurbaxani 1990; Takada and Jain 1991; Talukdar et al. 2002). Less is known about the salient factors in the various states of diffusion.

There are unique issues associated with digital wireless technologies, particularly the digital wireless phone industry, which offers a rich environment to study the diffusion process. First, multiple digital wireless phone standards exist. Some of the widely used ones are Global Systems for Mobile Communications (GSM), Code Division Multiple Access (CDMA), Personal Digital Cellular
(PDC), and Personal Communications Service (PCS). Second, countries do not necessarily adopt the same standards. For example, integrated pan-European telecommunications regulatory policy has prescribed uniform adoption of GSM among European Union members, but the United States has opted for open competition among multiple standards in the market. This leads us to ask two important questions in this research: Does one wireless standard promote faster growth? Does a prescribed standardization regime increase adoption payoffs in the long-term? Finally, the diffusion of digital wireless phones is complicated by an existing installed base of analog wireless phones that may either enable or hinder the diffusion of digital wireless phone technology.

We propose a state-based theory of technology diffusion, which identifies three important states: introduction, partial diffusion, and maturity. We argue that there is likely to be a different set of influential drivers and possibly variations in the strength of individual drivers on diffusion growth from state to state. We will use two approaches to investigate a number of hypotheses about digital wireless phone diffusion. We use a modification of the Bass (1969) model, which has been proposed in (Dekimpe et al. 1998) to test a set of hypotheses that relate to technology diffusion. The modified Bass model theorizes that growth in diffusion is based on different forces that occur at different points in time. It characterizes diffusion with an increase in the cumulative number of adopters in a market in terms of two parameters: the first-year adoption level and the diffusion growth after the first year through the first state transition.

Our second approach uses a coupled-hazard survival model (Dekimpe et al. 2000). This model establishes critical diffusion states, and theorizes that growth in diffusion can be understood in terms of transition events that move the diffusion from one state to another. The measurement focus is the amount of time it takes to reach the next diffusion state: the duration. The theorized relationships are captured by variables that affect state-to-state diffusion speeds for the first state transition.
Some of the other research questions that we will address are as follows. What factors influence diffusion rates for digital wireless phones in various countries? What are the key drivers that characterize the first transition in the digital wireless phone diffusion process from introduction to partial diffusion? What kind of models and empirical techniques are appropriate to characterize different states of diffusion? Can this help us understand the underlying dynamics of state-based diffusion? What different kinds of insights do the modified Bass diffusion and coupled-hazard survival models generate for the first state transition?

**THEORY**

We first propose a state-based theory of diffusion. We argue that explanatory factors for adoption and diffusion may not uniformly influence the diffusion speed of a new technology throughout its entire diffusion process. Diffusion curves consist of various diffusion states, and so there may be a different set of factors associated with the speed of technological diffusion across those states.

**A State-Based Theory of Technology Diffusion**

Past diffusion research (e.g., Cragg and King 1993; Gurbaxani 1990; Iacovou et al. 1995), regardless of the innovations under investigation (e.g., communication networks, computing, electronic data interchange) and units of analysis (e.g., individuals, firms), has focused on establishing variables that contribute to faster diffusion without considering the fact that some variables may be more influential at certain times than others. This is an overly simplistic view. New technologies take several years to go through the entire diffusion process, so the same set of variables might not equally influence diffusion speed over time. Understanding the factors that are more important at which diffusion states, thus, is an issue of interest to researchers and practitioners.
Diffusion of innovation theory (Rogers 1995) conceptualizes the various states involved in the diffusion process, which follows an S-shaped pattern. The adoption rate is slow at first, but then rises quickly during a take-off period, and eventually levels off as the market demand gets saturated. Rogers suggests that adopters should be classified into five categories based on adoption timing. Innovators (the initial 2.5%) adopt first, followed by early adopters (the following 13.5%), the early majority (the next 34%), the late majority (34%), and finally laggards (the last 16%).

Network externalities involve perceived business value from a system or technology product that develops in the presence of an increasing number of users (Katz and Shapiro 1986). Products and services that experience stronger network externalities have recognizable complementarities (e.g., hardware, software, or networking services, including telephones, fax and digital wireless phones).

The variable growth rate throughout the diffusion process has been theorized to result from varying degrees of network externalities effects (Gurbaxani 1990; Rai et al. 1998). The influence of network externalities can be expected to be weak when the technology is introduced to the market. But, an increase in adopters over time will create critical mass, generating stronger network effects. Eventually, the growth rate will decline as a saturation number of adopters is reached.

International product diffusion has been widely investigated using the Bass diffusion model. The emphasis has been on finding constructs that help to forecast future product sales and predict the diffusion trajectories of products. These empirical studies also have reported the influence of country characteristics (Dekimpe et al. 2000; Gruber and Verboven 2001a; Takada and Jain 1991), the timing of product introduction (Takada and Jain 1991), the installed base and prices of an earlier generation product (Danaher et al. 2001; Islam and Meade 1997), and word-of-mouth effects (Talukdar et al. 2002) on the speed of product diffusion across countries.

Although IS researchers have studied adoption and diffusion since the 1980s, most of the work
has occurred at individual, group, and organizational levels of analysis. More recently, several IS researchers have pursued an understanding of the influential factors throughout the diffusion process across countries (e.g., Gurbaxani 1990; Kraemer and Dedrick 2000; Rai et al. 1998). Economic factors and financial resources, the regulatory and legal policy environment, and information infrastructure are also reported to have an influence on the cross-country diffusion of e-commerce and the Internet (Kraemer et al. 2002; Wolcott et al. 2001). However, most studies have been conceptual frameworks, involving supporting case studies and country and regional reports.

**Technology Standards**

The *theory of standards and standardization* helps us to understand the underlying dynamics of the technology diffusion environment when multiple standards coexist, and to gauge the influence of standards-making on markets, competition, and innovation. Standards are important in information systems because they ensure that complimentary products (e.g., an operating system and related application software) and systems can work together. Technology standards and their impacts on markets, competition, and innovation have been extensively investigated (e.g., Besen and Farrell 1994; David and Greenstein 1990; Farrell et al. 1992; Matutes and Regibeau 1989). A *standard* refers to a set of technical specifications that producers adopt voluntarily or in accordance with formal agreements or regulatory authority (David and Steinmueller 1994). Standards related to IS are referred to as *compatibility standards* or *interface standards* (Antonelli 1994).

The process by which technologies become standardized results in outcomes that are observed in industry practice. These are called *de facto standards*. Standards that result from the rule of law are *de jure standards*. But *de facto* standards emerge from market-mediated processes that involve interactions among individuals, organizations and firms, industries and industrial clusters, and government and national-level representative associations (David 1987). Network externalities,
uncertain expectations on the part of different agents in the economy, and adoption inertia in the market often induce new users to adopt technology standards chosen by previous adopters.

In the digital wireless phone area, an ongoing battle for supremacy in the United States among the GSM, CDMA, and PCS standards is a good illustration of a market-mediated standardization process. Another illustration is Microsoft’s Windows XP as a de facto standard for PC operating systems in the United States and Europe, and the contrasting governmental push for adopting Linux operating system in the People’s Republic of China. The latter is aimed at reducing the required intellectual property rights payments to Microsoft. De jure standards, in contrast, are enforced by legal agreements in an economy, or they are mandated by standard-setting agencies. The GSM standards mandated by the European Union for member countries to adopt is a case in point. Also, China has been developing its own standard for digital video disks—the extended DVD standard or “EVD.” This will help Chinese manufacturers of DVDs to be able to avoid paying the intellectual property rights royalties on DVDs to the large Japanese firms that own the DVD patent rights.

The influence of standards and standardization on competition and innovation is a complex issue. Standards increase competition by reducing entry barriers and lowering market prices, and enhance demand by reducing consumer uncertainty and risks. This speeds up the diffusion process. De facto standards, in contrast, can make it more difficult for rival firms or new entrants to compete with firms that control a dominant standard, and de jure standards can block new entrants altogether. This may lead to stagnant innovation and a concomitant social welfare loss. By the same token, multiple standards in the marketplace may help to increase competition and force technology providers to constantly improve their technology, resulting in lower product and service prices for consumers, which, in turn, will lead to increased adoption.

Other research (Gruber and Verboven 2001a) reported on effects of standards on the process of
technology diffusion. They identify how public policy interventions related to timing of entry licenses and standard setting affect the diffusion of wireless telecommunications industry. They found that competing standards slowed the diffusion of analog mobile telecommunications. They were not able to make a similar argument for digital wireless technologies because of limited geographical observations and the short period for the data. Their results bear importantly on this research.

Our research extends Gruber and Verboven’s study. First, we consider a comprehensive set of factors and variables, including country-specific characteristics, industry-related variables, and policy interventions, and then collectively test their influence on the diffusion of digital wireless phones. Second, we provide a more in-depth explanation of the factors that drive diffusion growth with our state-based theory of diffusion, focusing specifically on the role of standards.

**Technology Policy**

The *technology policy* literature provides a basis for understanding how diffusion is influenced by business policies and regulatory interventions. Government policies and interventions play an important role in the diffusion of new technologies, especially networking technologies such as the Internet, and the emerging digital wireless telecommunications (Hargittai 1999; Kraemer et al. 2002; Montealegre 1999; Wolcott et al. 2001). Unlike stand-alone technologies, networking technologies requires large-scale network services and infrastructures before any provision of services occurs. Digital wireless phone operators require designated broadcast spectrums from the pooled resources of a country. These need to be appropriated through mechanisms chosen by a government (e.g., spectrum auctions, centrally-planned apportionment, etc.). As a result, government actions, such as licensing of service operators, preventive mechanisms for anti-competitive behavior, and price regulation are inevitable in the digital wireless phone environment. Also, regulatory practices governing competition through licensing have increased the diffusion of wireless communications in
fifteen European countries (Gruber and Verboven 2001b).

We identified two related streams of research on technology policy and IT innovations in the IS literature. The first stream includes a framework of institutional intervention in IT innovation (King et al. 1994) and other validating studies. The second stream involves the researchers’ own models to investigate the link between government policy and IT diffusion.

King et al. proposed a theoretical framework of the role of governments and other institutions in IT innovation through their influence and regulatory powers. They consider both the production and the uses of innovation. They categorize institutional actions into six classes: knowledge building, knowledge deployment, subsidies, mobilization, standard-setting, and innovation directives. This framework was validated in a study of Internet adoption in four Latin American countries (Montealegre 1999). Institutional actions facilitated Internet adoption, and that appropriate interventions during different phases of the adoption process are essential for successful technology diffusion. For example, standard-setting that prescribes ways of doing things contributes the most in the early phase of adoption. However, the dissemination of new knowledge about the innovation contributes the most in the later phases of the adoption process.

Similarly, the second stream of research on government policy and IT diffusion finds support for the influence of government policy on diffusion. National policy on telecom liberalization, promotion, and legislation has been significant in promoting the use of e-commerce in ten developed and developing nations (Kraemer et al. 2002). Also, government regulations have been found to be important determinants of Internet diffusion in 25 different countries (Wolcott et al. 2001).

Taken together, the two streams of research strongly suggest that government policy has implications for the outcomes of technology diffusion. The streams also prompt us to expect to observe different policies at play depending on the context (i.e., a set of countries or a type of IT).
However, all of the studies that we have cited here use detailed case studies to establish the relationship between technology policy and the diffusion process. Additional evidence from empirical studies can further delineate the influence of technology policy on IT diffusion.

**MODEL AND RESEARCH HYPOTHESES**

We next discuss a new theoretical model of international diffusion for digital wireless phone technology. We propose that the international diffusion of digital wireless phones is influenced by four dominant factors: *country environmental factors*, *digital wireless phone industry environmental factors*, *analog wireless phone industry environmental factors*, and *technology policy factors*.

**The Influence of Country Environmental Factors**

The role of country environmental factors on product and technology diffusion has identified GNP per capita (Dekimpe et al. 1998; Kiiski and Pohjola 2002; Kraemer et al. 2002; Talukdar et al. 2002), cosmopolitanism (Gatignon et al. 1989; Helsen et al. 1993), population homogeneity (Talukdar et al. 2002), education (Kiiski and Pohjola 2002), geography and demographic characteristics (Kraemer et al. 2002; Wolcott et al. 2001), and adequacy of financial, technological, and human resources (Kraemer et al. 2002; Wolcott et al. 2001). These studies suggest that country factors have a significant influence on product and technology diffusion.

Generally, new technologies are introduced first and diffuse more widely in richer countries which have financial, human, and infrastructure capabilities to invest and support the use of these technologies. E-commerce technology is an example, which shares similarities with digital wireless phone technology. Both require large-scale investment in computing and networking infrastructure before adoption can ensue. GDP per capita is a key driver of Internet-based sales across countries (International Telecommunication Union 2001). Countries with a higher GDP per capita (e.g., Japan,
Sweden and the United States) lead in e-commerce sales. Countries that have lower GDP per capita (e.g., Chile, India, Indonesia) appear to lag behind. Recently, the Economist Intelligence Unit released its 2003 “e-readiness ranking” (Economist Intelligence Unit 2003). The rankings rate countries on their opportunities to conduct e-commerce, taking into account IT infrastructure quality, business environment, legal and policy environment, and consumer and business adoption of the Internet. Countries (e.g., Denmark, Germany, Netherlands, Singapore) that receive high scores on connectivity and technology infrastructure (based on affordability, quality, and reliability of communications services) also have more widespread adoption of e-commerce among individuals and businesses. Based on these arguments, we assert the following hypotheses:

- **Hypothesis 1A (Country Wealth Hypothesis):** A country’s wealth has a positive influence on digital wireless phone diffusion speed.

- **Hypothesis 1B (Technology Infrastructure Hypothesis):** A country’s technology infrastructure has a positive influence on digital wireless phone diffusion speed.

**The Influence of Digital Wireless Phone Industry Environmental Factors**

We identify three digital wireless phone industry constructs that may affect adoption decisions and diffusion. The degree of competition in the market, reflected in lower product and service prices, is one of the determinants that influence decisions to adopt a new technology. For network technologies, due to positive externality effects, the number of adopters also factors into adoption decision making. The incremental benefits to users accrue relative to the number of existing adopters. Whether the number of standards drives adoption decisions also is worth investigating. A concern for adopters in a market that has more than one relevant technology standard is whether there are opportunities to consume services that are compatible across the standards. Consequently, when there are multiple standards in the marketplace, this might make consumers refrain from making adoption decisions. Thus, we propose the following hypotheses:
Hypothesis 2A (Digital Wireless Phone Industry Competitiveness Hypothesis): The degree of competitiveness of the digital wireless phone market has a positive influence on diffusion speed.

Hypothesis 2B (Existing Digital Wireless Phone Installed Base Hypothesis): A larger number of existing digital wireless phone adopters has a positive influence on diffusion speed.

Hypothesis 2C (Multiple Digital Wireless Standards Hypothesis): A larger number of digital wireless phone standards has a negative influence on diffusion speed.

The Influence of Analog Wireless Phone Industry Environmental Factors

Digital wireless phone technology offers improvements over the older analog wireless phone technology. They include a substantial increase in the number of subscribers and better communications quality. The digital technology will replace the existing installed base of analog technology over time. In the meantime, where both generations overlap in the market, the superiority of digital technology may prompt a range of different reactions from analog wireless phone operators and users. Analog operators may intensify the competition by lowering prices to attract additional users, slowing down the diffusion of digital wireless. Savvy analog wireless phone users also may decide to upgrade. Thus we propose the following hypotheses:

Hypothesis 3A (Analog Wireless Phone Industry Competitiveness Hypothesis): The degree of competitiveness in the analog wireless phone operators market has a negative influence on digital wireless phone diffusion speed.

Hypothesis 3B (Existing Analog Wireless Phone Installed Base Hypothesis): A larger number of existing analog wireless phone adopters has a positive influence on digital wireless phone diffusion speed.

Hypothesis 3C (Multiple Analog Wireless Standards Hypothesis): A larger number of analog wireless phone standards has a positive influence on digital wireless phone diffusion speed.

The Influence of Technology Policy Factors

There is considerable support in the literature on a linkage between government policies and interventions on technology diffusion (e.g., King et al. 1994; Kraemer et al. 1992; Kraemer et al. 2002; Montealegre 1999). However, the technology policy variables tested differs across studies. Yet
there are a few criteria to suggest appropriate policy variables. The results from testing the policy variables should identify policy and managerial implications that influence the diffusion process of the technology. Also, there should be differences in the observed policy practices across a set of countries for new knowledge to emerge. In the context of digital wireless phones, standardization and competition policy fit these criteria.

The issue of market-mediated versus regulated standards has been observed and studied in many industries (e.g., high-definition televisions). However, there is no agreement in the academic literature on how policy makers’ decisions on standardization in such network industries as digital wireless phones will influence the diffusion process. Similarly, in practice, different countries have different beliefs about how standards should emerge. Some, such as the United States, act as though they believe that markets create standards. Others, such as the European countries, believe the opposite: standards create markets. These decisions are likely to have direct and indirect impacts on adoption decisions through service availability, and technological development and coverage.

Competition policy is likely to influence adoption decisions and diffusion speed. Competition policy decisions involve the number of operator licenses, service coverage of operators, and licensing fees. We hypothesize that:

□ **Hypothesis 4A (Standardization Policy Hypothesis):** Market-mediated standards and regulated standards policies will exhibit different influences on digital wireless phone diffusion speed.

□ **Hypothesis 4B (Competition Policy Hypothesis):** Competition policies, including the number of operator licenses and operator service coverage, will exhibit different influences on digital wireless phone diffusion speed.

**MODEL ESTIMATION AND DATA**

We next discuss how we conceptualize the diffusion states, and then explain the models and
estimation methods we use, as well as the data we will analyze.

**Modeling Preliminaries**

We define *diffusion states* as periods in time for which there are likely to be different factors influencing the diffusion rates of a technology. Rogers has written that diffusion increases gradually before a critical mass of adopters decides to adopt and then rises quickly after critical mass has been reached. This suggests an operational partitioning of diffusion states: *Introduction*, *Partial Diffusion*, and *Maturity*. The *Introduction State* is the time when a country begins its digital wireless phone adoption. The *Partial Diffusion State* is the time when critical mass in the market has been reached.

Adoption rates vary from one innovation to another (Rogers 1995). Rogers suggests that critical mass typically occurs when approximately 10% to 20% of adopters have adopted. With this in mind, we have set the critical mass of digital wireless phone adoption at 15% of all adopters. The *Maturity State* occurs when the market saturation point has been reached (Dekimpe et al. 2000). Digital wireless phones, introduced in the 1990s, will take time to reach the *Maturity* state. We will focus on factors that affect diffusion speed from the *Introduction State* to the *Partial Diffusion State*.

We use a *modified Bass model* (Dekimpe et al. 1998) and a *coupled-hazard survival model* (Dekimpe et al. 2000) to model state-wise diffusion. (See Table 1 and Figure 1.)

**Figure 1. Models of International Diffusion of Digital Wireless Phone Technology**
The modified Bass model provides explanatory factors that contribute to diffusion growth in the first and following years. It serves as an appropriate point of comparison to validate the results that we have obtained from the coupled-hazard survival model. A survival model offers a different estimation approach and different managerial insights. In addition to identifying variables that influence diffusion speed, the coupled-hazard survival model identifies how the probability of reaching a diffusion state changes as the values of covariates change over time.

Table 1. Contrasting Empirical Models

<table>
<thead>
<tr>
<th>MODEL ELEMENTS</th>
<th>MODIFIED BASS MODEL</th>
<th>COUPLED-HAZARD SURVIVAL MODEL</th>
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<tr>
<td><strong>MODEL ELEMENTS</strong></td>
<td><strong>BASIC MODEL</strong></td>
<td><strong>LOGISTIC MODEL</strong></td>
</tr>
<tr>
<td>Dependent variable</td>
<td>Number of adopters from the Introduction State to the Partial Diffusion State or end of observation</td>
<td>First-year adoption level and diffusion growth</td>
</tr>
<tr>
<td>Independent variable</td>
<td>Social system size, long-run ceiling, and cumulative adopters</td>
<td>Proposed explanatory variables</td>
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<td>Estimated parameters</td>
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<tr>
<td>Estimation method</td>
<td>Non-linear least squares</td>
<td>Non-linear least squares</td>
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A Modified Bass Model

The Bass model suggests that new product adoption is driven by two factors: a coefficient of external influence, including factors other than the influence of existing adopters, and a coefficient of internal influence, representing the social influence of the existing adopters. The model’s likelihood that an individual will adopt a new product at time $t$, given that he has not yet adopted, is a linear function of the number of existing adopters: $h(t) = \frac{f(t)}{1 - F(t)} = p + qF(t)$. $h(t)$ is the hazard rate or the likelihood to adopt at time $t$, given that no adoption has occurred in the time interval $(0, t)$. $f(t)$ and
$F(t)$ denote the probability density and cumulative density function at time $t$. $p$ and $q$ are the coefficients of external and internal influence, with $0 < p$ and $q < 1$. Since we often observe an aggregate number of adopters, not an individual’s adoption behavior, the hazard model is specified with the number of adopters as $n(t) = \left( p + \frac{q}{m} N(t) \right) \left( m - N(t) \right)$, where $n(t) = m f(t)$ is the number of adopters at time $t$, $N(t)$ is the cumulative number of adopters at time $t$, and $m$ is the market potential for adoption.

The Bass model limits the comparison of diffusion parameters across countries (Dekimpe et al. 1998). Why? First, the Bass model uses a time-series of the number of adopters to estimate the diffusion parameters. As a result, small and large countries with same number of adopters over time will have the same diffusion parameters. This is unlikely to be correct, so it is a mistake to build this assumption into an estimation model for the diffusion pattern (other than as a baseline). Second, by using fixed time periods for all countries in a data set, there is a risk of left-hand truncation bias. This causes the estimates of the first-year adoption level of the diffusion curve to be inflated for countries that start to adopt earlier than the time frame represented by the data.

To address these limitations, Dekimpe et al. (1998) proposed a modified Bass model for country $i$ as $n_{i,t} = \left[ \left( \frac{n_{i,1}}{C_i S_i} \right) + B_i \left( \frac{N_{i,t-1}}{C_i S_i} \right) \right] \left[ C_i S_i - N_{i,t-1} \right]$. $n_{i,t}$ is the number of adopters at time $t$, $N_{i,t-1}$ is the cumulative number of adopters up to time $t-1$, $S_i$ is the social system size or population within which a technology diffuses, $C_i$ is the long-run penetration ceiling or maximum proportion of the population that will adopt stated as a percentage of adopters, and $B_i$ is the diffusion growth rate. The diffusion curve intercept $\left( \frac{n_{i,1}}{C_i S_i} \right)$ is also referred to as the parameter, $A_{i,t}$, and represents the first-year adoption level. The four parameters—the social system size, the long-run penetration ceiling, the first-year
adoption level, and the growth rate—are used to explain variation in diffusion patterns across countries. Parameters $A_{i1}$, $B_i$, and $C_{Si}$ are similar to the parameters $p$, $q$, and $m$ in the Bass model.

This model offers some advantages. First, separating the market potential into two variables (the social system size, and the long-run penetration ceiling) enables researchers to accurately identify sources of variation in diffusion patterns among countries. Second, the alignment of countries’ introduction time of a technology (instead of calendar times) permits the estimates of the first-year adoption level across countries to have the same interpretation. Thus, it allows valid comparisons.

Factors that govern the dynamics of social systems and long-run penetration ceiling are exogenous to the technology that is diffusing, yet they nevertheless will control the extent of the diffusion that is observed. Although the modified Bass model was designed to examine the diffusion process overall, it is flexible enough to estimate state-based diffusion parameters by limiting observations to those defined by the diffusion states of interest. To test the influence of the explanatory variables on the first-year adoption level and the diffusion growth rate, we use two logistic models to ensure that $A_{i1}$ and $B_i$ are between 0 and 1: 

$$A_{i1} = \frac{1}{1 + e^{-\alpha_i}} , \quad B_i = \frac{1}{1 + e^{-\beta_i}} ,$$

where $\alpha$ and $\beta$ are vectors of parameters and $X_i$ is a vector of explanatory variables.

**A Coupled-Hazard Survival Model**

Diffusion states for a technology are not independent from each other. There is a natural order embedded in the diffusion process that is readily recognized, and suggested by prior research. For example, a country has to start from the Introduction State, and then proceed to the Partial Diffusion State, before it can finally reach the Maturity State at some later time. We use a coupled-hazard model (Dekimpe et al., 2000) to set up such interdependencies across the diffusion states.
The coupled-hazard model characterizes transitions that a country has to traverse from state-to-state leading to the full adoption of a technology. **Diffusion states** and **transition rates** are the two key elements in the model. We model **time until Partial Diffusion** and **time until Maturity** as two **interdependent** failure-time processes. Each process has two possible values: 0 means that neither **Partial Diffusion** nor **Maturity** has been achieved; 1 means that either **Partial Diffusion** or **Maturity** has been reached. As a result, we have: **State [0,0]**—no **Partial Diffusion** or **Maturity** has been reached; **State [0,1]**—no **Partial Diffusion** has been reached but **Maturity** has been achieved, **State [1,0]**—**Partial Diffusion** has been reached but not **Maturity**; and finally **State [1,1]**—both **Partial Diffusion** and **Maturity** have been reached. To maintain **logical consistency** in our representation of the diffusion process for the coupled hazard model’s econometrics, we drop **State [0,1]**: a country cannot reach **Maturity** without going through **Partial Diffusion**. This leaves three states, the **Introduction State [0,0]**, the **Partial Diffusion State [0,1]**, and the **Maturity State [1,1]**.

The dynamics of the diffusion process are depicted with **transition rates**, the likelihood in time that a country will move from one diffusion state to another. With three diffusion states, there are six possible transition rates based on \(R(R-1)\), where \(R\) is the number of states, as shown in Figure 2.

**Figure 2. A Fully-Specified Coupled-Hazard System (3 States, 6 Transition Rates)**

The **reduced coupled-hazard system** for the international diffusion of digital wireless phones with three diffusion states and two transition rates is illustrated in Figure 3.
Figure 3. A Reduced Coupled-Hazard System (3 States, 2 Transition Rates)

Since an empirical regularity in the observed data is that a country never falls back to an earlier state on the diffusion curve, we can eliminate the dashed-line transitions in Figure 2. We can also remove the dotted-line transition that jumps from the Introduction State to the Maturity State.

Coupled-Hazard Model Estimation Methods

Reaching a new diffusion state and the characteristic transition rates are analogous to events and hazard rates. The hazard rate is the probability of reaching a new diffusion state at time $t$, given that a country has not reached that diffusion state before that. This suggests survival analysis methods for an empirical test of the main hypotheses in this research. We will use parametric survival methods (an explanatory approach, as opposed to descriptive non-parametric survival methods like the Kaplan-Meier estimator) to evaluate the factors that affect transition rates. We analyze a proportional hazard model (Cox and Oakes 1984) to estimate the effects of covariates on diffusion speed. It specifies the hazard for technology diffusion for country $i$ at time $t$ as the product of a baseline hazard function and a multiplicative function of a row vector of explanatory variables, $X$: $h_i(t) = \delta_0(t)e^{X^\beta}$. $h(t)$ is the hazard function, $\delta_0(t)$ the baseline hazard function, and $\beta$ the column vector of regression coefficients.

Proportional hazards assume that the relative hazard of the two countries $i$ and $j$ is constant across time, when the explanatory variables $X_i$ and $X_j$ do not change over time: $h_i(t|X_i) = \frac{\delta_0(t)e^{X_i^\beta}}{\delta_0(t)e^{X_j^\beta}} = e^{X_i^\beta}$. $h(t)$ (Therneau and Grambsch 2000). So with time-varying variables, the relative hazard for two countries
will not be independent of time; the impacts will be reflected in a single coefficient $\beta$.

By taking the logarithm of the hazard function, we get a familiar regression model,

$$\log h_i(t) = \delta(t) + X \beta.$$  
We selected the Weibull specification with two parameters, $\alpha$ and $\lambda$, for our baseline hazard function: $\delta_0(t) = \alpha \lambda t^{\alpha-1}$. This makes sense because unlike other functions (e.g., exponential, log-logistic), a Weibull baseline hazard matches the monotonically increasing function of the diffusion curve. Estimating the model yields maximum likelihood estimates for the explanatory variables, so we can determine whether the observed effects are consistent with the hypothesized effects. Such estimation also yields a reading on the hazard of a country’s conditional probability of transition from state-to-state in the diffusion process for digital wireless phones. The estimates of the parameters tell us the percentage changes in the hazard rate for a one unit change in an explanatory variable. The model permits us to explain why adoption is occurring and how its conditional probability changes over time via $e^{\lambda \beta}$.

Data and Research Context

We collected annual data for the model variables. Countries started their digital wireless phone implementation in different years, from 1992 to 1997. All of the observations ended in 1999. The data represent the diffusion of digital wireless phones and the corresponding explanatory variables in 45 developed and developing countries in Europe, Asia, Africa, and North America.1 Data sources include international organizations such as the International Telecommunication Union (ITU), the World Bank and the United Nations (UN). We also obtained data from the countries’ regulatory Web sites and private databases and publications, such as the Gartner Group, Wireless Week magazine, the

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1 The 45 countries included are Australia, Austria, Belgium, China, Cyprus, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Italy, Japan, Jordan, Korea, Kuwait, Luxembourg, Malaysia, Morocco, Netherlands, New Zealand, Nicaragua, Norway, Pakistan, Philippines, Portugal, Russia, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, United Arab Emirates, United Kingdom, United States, and Vietnam.
Global System for Mobile Communications (GSM) Web site (www.gsmworld.com), and the Code Division Multiple Access (CDMA) development group Web site (www.cdg.org).

RESULTS AND DISCUSSION

We next describe the estimation results from the models, interpret the related common and contrasting insights, and identify the broader implications of this research for theory and practice.

RESULTS OF THE MODIFIED BASS MODEL

To estimate the models, we set the potential adopter population for social system size, $S$, multiplied by the long-term penetration ceiling, $C$, to the total population of a country in the year when the country’s diffusion of digital wireless phones began. We used the logistic model to estimate the effect of explanatory variables on first-year adoption. We parameterized the logistic transformation of the growth rate in the modified Bass model to estimate the explanatory variables. Table 2 summarizes the factors that affect the first-year adoption level and growth rate parameters in the modified Bass model. There are more significant variables for the estimation of the first-year adoption level than for the growth rate estimation.

We first discuss the results of the first-year adoption level estimation. The effect of GNP per capita ($\alpha_{\text{GNP}} = -0.001$, std. dev. = .001, $p < .10$) is close to zero, so its effect on the first-year adoption level is small. All of the digital wireless phone variables are significant. Consistent with our expectation, the number of digital wireless phone standards has a negative effect ($\alpha_{\text{DIGITAL_STD}} = -16.55$, std. dev. = 8.27, $p < .05$) on the first-year adoption level. Digital wireless phone competition is characterized by the number of operators and the service prices. The number of operators is a positive driver of first-year adoption ($\alpha_{\text{DIGITAL_OPR}} = 5.82$, std. dev. = 3.25, $p < .10$), and that lower service prices lead to faster first-year adoption ($\alpha_{\text{DIGITAL_PRC}} = -0.09$, std. dev. = 0.05, $p < .10$).
Similarly, the analog wireless phone variables related to competition also explain first-year adoption. Consistent with our hypotheses, more competition in the analog wireless market, in terms of a higher number of operators ($\alpha_{\text{ANALOG\_OPR}} = -23.04$, std. dev. = 11.77, $p < .10$) and lower service prices ($\alpha_{\text{ANALOG\_PRC}} = 0.09$, std. dev. = 0.06, $p < .10$), has a negative effect on the first-year adoption of digital wireless phones. In addition, a higher number of analog wireless phone standards has a positive effect on the first-year adoption of digital wireless phones ($\alpha_{\text{ANALOG\_STD}} = 4.38$, std. dev. = 2.05, $p < .05$). Finally, higher analog wireless phone penetration has a positive effect ($\alpha_{\text{ANALOG\_PEN}} = 5.12$, std. dev. = 2.85, $p < .10$) on the extent of first-year adoption of digital wireless phones. None of the variables related to technology policy were significant.

There are three significant explanatory variables for the growth rate. The number of digital wireless phone operators is positive and significant ($\beta_{\text{DIGITAL\_OPR}} = 4.90$; std. dev. = 2.80; $p < .10$). This suggests that the diffusion growth rate appears to be faster in a more competitive market. In contrast, the number of analog wireless phone operators is negative and significant ($\beta_{\text{DIGITAL\_OPR}} = -16.82$; std. dev. = 9.81; $p < .10$). Higher competition in the analog wireless phone industry slows down the growth of digital wireless phone diffusion. Finally, similar to the result for the first-year adoption level, the number of analog wireless phone standards is positive and significant ($\beta_{\text{ANALOG\_STD}} = 18.23$; std. dev. = 10.32; $p < .10$). This supports our hypothesis that a higher number of analog wireless phone standards speeds up the growth of digital wireless phone diffusion.
Table 2. Modified Bass Model Results

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>FIRST-YEAR ADOPTION (A_{t})</th>
<th>GROWTH RATE (B_{t})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COEFFICIENT</td>
<td>STANDARD ERROR</td>
</tr>
<tr>
<td>GNP</td>
<td>-0.001*</td>
<td>0.001</td>
</tr>
<tr>
<td>DIGITAL_PEN</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>DIGITAL_OPR</td>
<td>5.82*</td>
<td>3.25</td>
</tr>
<tr>
<td>DIGITAL_STD</td>
<td>-16.55**</td>
<td>8.27</td>
</tr>
<tr>
<td>DIGITAL_PRC</td>
<td>-0.09*</td>
<td>0.05</td>
</tr>
<tr>
<td>ANALOG_PEN</td>
<td>5.12*</td>
<td>2.85</td>
</tr>
<tr>
<td>ANALOG_OPR</td>
<td>-23.04*</td>
<td>11.77</td>
</tr>
<tr>
<td>ANALOG_STD</td>
<td>4.38**</td>
<td>2.05</td>
</tr>
<tr>
<td>ANALOG_PRC</td>
<td>0.09*</td>
<td>0.06</td>
</tr>
<tr>
<td>STD_POL</td>
<td>-8.24</td>
<td>5.03</td>
</tr>
<tr>
<td>LICENSE1</td>
<td>4.65</td>
<td>6.39</td>
</tr>
<tr>
<td>LICENSE2</td>
<td>17.07</td>
<td>10.86</td>
</tr>
</tbody>
</table>

Note: First-year adoption model $R^2 = 0.63$; growth rate model $R^2 = 0.72$. Significance levels for the explanatory variable are given by: * = $p < .10$, ** = $p < .05$, and *** = $p < .01$. GNP per capita (GNP) and the number of fixed line phones per 1000 inhabitants (PHONE) are highly correlated ($\rho = 0.91$), so we dropped PHONE from the model. All variance inflation factors (VIFs) of the rest of covariates are lower than 10, showing no presence of multicollinearity. Cumulative digital wireless phone penetration (DIGITAL_PEN) is not applicable in the first-year adoption model (NA). Since the growth rate model is nested in the modified Bass model, which has the cumulative number of adopters as an independent variable, we excluded DIGITAL_PEN from this model. To check for the correlation (association) of the binary variables, we used Cramer’s V, a $\chi^2$-based measure of association ranging from 0 to 1. We recoded the two licensing policy variables (LICENSE1, LICENSE2) to a new variable that has three values corresponding to regional, national, and hybrid licensing policy in the original variables. The association between standards policy (STD_POL) and licensing policy is not high; Cramer’s V = 0.391. This is sensitive to sample size and the number of different values that the variable can take on. We also checked the Goodman-Kruskal $\lambda$-value (also in 0 to 1 range), the percentage reduction in errors in predicting values of one variable given knowledge of the other. The $\lambda$-value = 0.125, indicating a low association between standards policy (STD_POL) and licensing policy.

Results of the Coupled-Hazard Survival Model

Table 3 presents the results of the coupled-hazard survival model estimation. The model has a likelihood ratio of 60.63 ($p = 0.00$), an indication of high fit. (See Table 3.)
Table 3. Coupled-Hazard Survival Model Results

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>COEFFICIENT</th>
<th>STANDARD DEVIATION</th>
<th>HAZARD RATIO</th>
</tr>
</thead>
<tbody>
<tr>
<td>GNP</td>
<td>-0.00007</td>
<td>0.00005</td>
<td>0.9999</td>
</tr>
<tr>
<td>DIGITAL_PEN</td>
<td>0.32***</td>
<td>0.08</td>
<td>1.38</td>
</tr>
<tr>
<td>DIGITAL_OPR</td>
<td>0.25</td>
<td>0.28</td>
<td>1.29</td>
</tr>
<tr>
<td>DIGITAL_STD</td>
<td>-1.60</td>
<td>1.22</td>
<td>0.20</td>
</tr>
<tr>
<td>DIGITAL_PRC</td>
<td>-0.11**</td>
<td>0.05</td>
<td>0.89</td>
</tr>
<tr>
<td>ANALOG_PEN</td>
<td>0.05</td>
<td>0.07</td>
<td>1.05</td>
</tr>
<tr>
<td>ANALOG_OPR</td>
<td>-1.10</td>
<td>0.70</td>
<td>0.33</td>
</tr>
<tr>
<td>ANALOG_STD</td>
<td>-1.92*</td>
<td>1.13</td>
<td>0.15</td>
</tr>
<tr>
<td>ANALOG_PRC</td>
<td>0.10**</td>
<td>0.04</td>
<td>1.10</td>
</tr>
<tr>
<td>STD_POL</td>
<td>-1.73**</td>
<td>0.83</td>
<td>0.18</td>
</tr>
<tr>
<td>LICENSE1</td>
<td>-3.78**</td>
<td>1.63</td>
<td>0.02</td>
</tr>
<tr>
<td>LICENSE2</td>
<td>-3.31**</td>
<td>1.46</td>
<td>0.04</td>
</tr>
<tr>
<td>α</td>
<td>7.73***</td>
<td>1.51</td>
<td>NA</td>
</tr>
<tr>
<td>λ</td>
<td>0.0002***</td>
<td>2.54</td>
<td>NA</td>
</tr>
</tbody>
</table>

Note: Likelihood ratio, model significance = 60.63***. Significance levels of the explanatory variables are given by $p < .10 = *, p < .05 = **,$ and $p < .01 = ***$. “NA” means “not applicable.”

Two digital wireless phone industry environment variables (DIGITAL_PEN, DIGITAL_PRC) are significant. The influence of digital wireless phone penetration is positive and highly significant ($\beta_{\text{DIGITAL_PEN}} = 0.32; \text{std. dev.} = 0.08; p < .01; \text{hazard ratio of } e^{\beta_{\text{DIGITAL_PEN}}} = 1.38$). This means that a 1% increase in digital wireless phone penetration will increase the hazard rate of reaching the *Partial Diffusion State* by 38%. Higher digital wireless phone service prices slow down diffusion speed ($\beta_{\text{DIGITAL_PRC}} = -0.11; \text{std. dev.} = 0.05; p < .05; \text{hazard ratio} = 0.89$), so a unit price increase in digital wireless phone service prices decreases the hazard rate by about 11%.

Consistent with the results from the modified Bass model, higher analog wireless phone service prices promote faster diffusion speed of digital wireless phone diffusion ($\beta_{\text{ANALOG_PRC}} = 0.10; \text{std. dev.} = 0.04; p < .05; \text{hazard ratio} = 1.10$). So, a unit increase in analog wireless phone service prices increases the hazard rate to achieve the *Partial Diffusion State* of digital wireless phone diffusion by
10%. However, in contrast to our hypothesized effect and the results from the modified Bass model, the higher number of analog wireless phone standards appear to slow digital wireless phone diffusion speed ($\beta_{\text{ANALOG\_STD}} = -1.92; \text{ std. dev.} = 1.13; p < .10; \text{ hazard ratio} = 0.15$). In particular, an additional analog wireless phone standard reduces the hazard rate of reaching the *Partial Diffusion State* of digital wireless phone diffusion by 85%.

All technology policy variables are significant. Countries that use market-mediated standardization policy (STD\_POL = 0) have faster diffusion speed of digital wireless phones than those that use regulated standardization policy (STD\_POL =1) ($\beta_{\text{STD\_POL}} = -1.73; \text{ std. dev.} = 0.83; \text{ p} < .50; \text{ hazard ratio} = 0.18$). This suggests that the hazard rate to reach the *Partial Diffusion State* of countries that use regulated policy is 18% of those that use market-mediated policy.

The coefficients of the two binary variables that measure licensing policy are negative and significant ($\beta_{\text{LICENSE1}} = -3.78; \text{ std. dev.} = 1.63; p < .05; \text{ hazard ratio} = 0.02; \beta_{\text{LICENSE2}} = -3.31; \text{ std. dev.} = 1.46; p < .05; \text{ hazard ratio} = 0.04$). So countries using regional licensing policy (LICENSE1=0, LICENSE2=0) are more likely to reach the *Partial Diffusion State* faster than those that use either national (LICENSE1=0, LICENSE2=1) or hybrid (LICENSE1=1, LICENSE2=0) licensing policies. In particular, the hazard rate to reach the *Partial Diffusion State* of countries that use national licensing policy is 4% of those that use regional licensing policy. Similarly, the hazard rate of countries that use hybrid licensing policy is 2% of those that use regional licensing policy.

**Discussion**

We used the first-year adoption level and the growth rate of diffusion beyond the first year to characterize diffusion speed in a modified Bass model to test for the effects of country environmental factors, digital and analog wireless phone environmental factors, and technology policy factors. The factors enable us to explain the speed of digital wireless phone diffusion from the *Introduction State*
to the Partial Diffusion State, emphasizing the role of technology standards in the mix. We modeled the dynamics of diffusion based on the likelihood of reaching the Partial Diffusion State in a coupled-hazard survival model. We used the hazard ratio to provide a measure of the change in the hazard rate with a one unit change in the value of a specific explanatory variable.

The Impacts of Variables That Are Not Related to Standards

Our results show that higher GNP per capita dampens the extent of first-year diffusion. This contradicts our expectation that rich countries should have a head start with diffusion. Our data show that GNP per capita has a strongly positive correlation ($\rho = 0.91$) with the number of fixed-line phones per 1000 people. This reflects the level of infrastructure development in countries. Lower GNP per capita countries appear to have limited availability of fixed land line phones and the related services. For example, according to the World Bank, Egypt, India, and Russia in 1999 had a waiting time of at least 28, 11, and 46 months, respectively, for subscribers to obtain land-line telephone connections. This may be because most fixed land-line operators in developing countries either are fully or partially-owned by governments. Also, the fixed land-line markets in several countries are subject to stricter regulation than the wireless markets are. Thus individuals and firms in countries with lower GNP per capita may be able to choose to adopt wireless phones as substitutes.

More competition in the digital wireless phone market, in terms of a larger number of operators and lower service prices, helps to expedite diffusion. Our estimation of the modified Bass model shows that the higher number of operators tends to increase the first-year adoption level, as well as spur the growth of adopters in the following years. An analysis done by the Organization for Economic Cooperation and Development (2002) also found that markets that have four or more operators experience faster growth than those with monopolies, duopolies, or three operators. Consequently, policy makers should be encouraging the formation of open markets for the current
generation of digital wireless phone technology, and coming generations of technology (e.g., 3G) too. Lower prices for digital wireless phone services also tend to increase the rate of diffusion and the likelihood that a country will reach the **Partial Diffusion State**.

According to the International Telecommunications Union (1999), most countries do not regulate wireless phone tariffs. Instead, a more common practice in several countries (e.g., Australia) is to have regulatory units (e.g., the Australian Competition and Consumer Commission) monitor the market for fair competition. Although the worldwide trend for wireless services prices is moving downward, there are several other strategies, including phone subsidies and prepaid services, which operators can employ to entice price-sensitive users to adopt in order to expand their markets.

Licensing policy appears to have different short-term and long-term impacts. During the first year, countries that use national licensing policy appears to lead to higher adoption than those that use hybrid and regional licensing policies. However, countries that use regional licensing policy tend to have a more rapid rate of diffusion after the first year. The results from our coupled-hazard survival model also confirm this long-term effect of licensing policy. This may be because regional operators are closer to their customers, in geographical and business relationship terms, and may be able to provide better services, as a result. So it appears to be more beneficial for countries that wish to achieve more rapid diffusion of digital wireless phones if policy makers initially permit operators to provide services in selected geographical areas. This is similar to what we have seen in the United States following the break-up of the AT&T telephone monopoly into regional companies that offered more competitive long-distance analog phone services. This industrial organization set the stage for regionally-focused digital wireless phone service offerings that have swept the American economy.

Consistent with the theory of diffusion of successive generations of technology (Norton and Bass 1992), several variables related to the analog wireless phone industry appear to affect the diffusion
growth of digital wireless phones. Countries with a higher level of analog wireless phone penetration appear to have higher levels of first-year adoption of digital wireless phones. This may be the result of the two co-occurring forces. First, some of the existing analog wireless phone users may decide to upgrade to the newer digital wireless phone technology when it becomes available. They may be responsive to a “push” from the digital service providers, who already have established a working relationship with the analog wireless phone services users. And, second, markets with more analog wireless phone users will have more consumers who may be more willing or express an interest to try out a related technology based on their experience with the earlier generation. This is a “pull” from the market. The more users of the analog wireless phone services there are, the easier it is for some (plus other new users) to adopt the digital wireless phone technology due to the positive externalities.

But competition from the analog wireless phone market, in terms of the number of analog wireless phone operators, also appears to slow down the diffusion speed of the digital wireless phone technology. Digital wireless phones, in the time frame to which our data apply, were viewed as new technologies. So the number of analog wireless phone operators could have created adoption inertia, because the operator firms were less willing to move to the new digital technology and forego revenue streams that would have continued from their analog wireless operations.

The Impacts of Standards-Related Variables

The influence of the number of analog wireless phone standards is ambiguous. The modified Bass model shows that more analog standards tend to increase the number of digital wireless phone services adopters in the first year, and it also promotes faster growth over the longer term. However, the addition of one analog standard appears to slow down the diffusion of digital wireless phone services; in fact, it reduces by 85% the likelihood of achieving the 15% penetration rate that is consistent with a transition to the Partial Diffusion State in our model. Similar to the explanation
that we offered above involving adoption inertia, we see again here the potential for a similar explanation. The greater the number of analog wireless standards in the market, the more diffuse are the expectations of the operators and market players who must make an effective business case to move on to the next generation of technology.

When markets are split among many standards, it is often the case that there is considerable uncertainty about the future trajectory of the technologies that are under observation. Senior managers, as a result, will need to wait to see which direction the market will go before making a subsequent commitment to another new technology. We think of this as the “work out” time that a market needs so that its participants’ expectations coalesce around the technologies that are most likely to represent the bulk of the adoption later on. With the way that expectations in the market are formed, split interest in a number of standards is as likely to create a between-generation impact as it is to create a within-generation impact with the adoption of digital wireless phone technologies.

Estimation of the modified Bass model and the coupled-hazard survival model both suggest that the presence in a national economy of more digital wireless phone standards tends to slow down the rate of technology diffusion. This may be because a single standard reduces the uncertainty that digital wireless phone services customers face when they adopt the new technology. A single standard is probably less confusing to potential users in the marketplace, and it will make the services offered by any individual digital wireless services operator more compatible with the systems offered by other operators. This increases the likelihood of larger externalities felt by users economy-wide.

Overall, the results associated with our analysis of standardization policy are consistent across the models. Countries that use a market-mediated policy have a higher adoption level of digital wireless phone services than countries that use regulatory policy throughout the diffusion process. This may be occurring for a related reason: because countries that use market-mediated policy have an average
of a 6% higher number of operators than countries that use regulatory policy. The extent of the competition may help to raise awareness of the business value of the technology, resulting in more adoption. Clearly, the choice of standardization has very important policy implications. This suggests that regulators should probably refrain from prescribing a specific standard for operators to use. Instead, they should let these firms, which have their own rational expectations and forecasts about how the standards will evolve and their own technology investments and future performance considerations, make their own decisions.

**LIMITATIONS**

For the reader to appreciate the contributions to new knowledge in this research, it is appropriate for us to discuss a number of its limitations. First, due to the unavailability of some international data, we have only 45 countries in our data set. In addition, our observations end in 1999. These limitations can be traced to constraints with obtaining data for time periods and for countries when no more up-to-date data had yet been obtained by the major international organizations that track technology investment and diffusion in developed and developing countries. The lag-time for these organizations to obtain accurate and useful international telecommunications-related diffusion data is two or three years—longer than what IS researchers typically experience with national-level and industry-level data on IT investments, IT productivity and technology-led economic performance. Nevertheless, we are continuing to add more countries to our data set and to expand the observation period to include recent years after 1999.

Second, all measures of the variables that populate our models represent annual data. This granularity of our observations with respect to time may not identify the actual point in time (say the month or the quarter) when a country actually reaches the Partial Diffusion State. To get more
accurate parameter estimates in a state-wise diffusion process, we recognize that there may be a need for monthly or quarterly data. But the currently available sources do not permit that, as is the case with most other data sets that require a significant amount of primary survey work or factual data collection at the country level across many nations.

A third limitation relates to our choices about coding the binary variables for technology and regulatory policy. A general concern about using binary variables is whether they can accurately represent what happens in the real world and whether their values have the same meaning across all observations. In our research, we use binary variables to capture licensing and standardization policy. Some might argue, for example, that the implementation of regional licensing policy in the United States may not be the same as that in countries like India. In India, the wireless phone service areas are divided into four “metros” (New Delhi, Mumbai, Chennai and Kolkata) and twenty “circles,” roughly equal to the states of India. Each metro and each circle is allocated two wireless phone licenses by the Indian regulatory agency. Understanding these kinds of implementation mechanism details is needed to for an even more in-depth understanding of the influence of the policy variables.

Fourth, we also should note the limitations associated with our modeling choices relative to the formulation of the Weibull proportional hazard model. There is a risk associated with specifying the baseline hazard with a Weibull distribution, because using an inappropriate specification may produce erroneous estimates of the regression coefficients. On the other hand, leaving the baseline hazard function unspecified, when we know its shape, will result in a loss of efficiency in the estimation of the regression coefficients. To evaluate if our choice of Weibull distribution closely matches with the underlying baseline hazard, we compared the estimated regression coefficients from the Weibull model with those from a semi-parametric Cox proportional hazard model, where the baseline hazard function is left unspecified. Our comparison shows that all estimated regression coefficients have the
same signs and any differences in magnitude appear to be very minor. We concluded, as a result, that
the Weibull specification is an appropriate choice for the baseline hazard function.

Fifth, another issue that deserves consideration is our use of the Rogers’ definitions for the states
of diffusion. Rogers’ representation of the different states of diffusion is descriptive, and the
percentages of observed adoption in a population that are used are not founded on specific theory or
modeling based evidence. Instead, the representation that is used in that research reflects judgment
calls on the part of the author. Although we have employed the definitions that Rogers’ has used, we
are also in the midst of using the analysis of empirical regularities for pattern recognition in the data
as a means to find other ways to represent the different states to redefine when transitions occur.

Finally, we wish to point out to the reader that there are still issues that relate to the findings of the
modified Bass model and the survival model that merit additional discussion. Why do we see
different results with the same data? How might the modeling choices related to the explanatory
variables drive the outcomes? Or can we see other reasons for the discrepancy in results? In what
ways might other aspects of the models we used cause this? In addition to the theoretical differences,
there are several different empirical regularities in the modified Bass model and the coupled-hazard
survival model. First, similar to the original Bass model, the modified Bass model builds an aggregate
diffusion model based upon an assumption about the adoption behavior of individuals. It assumes
that there are two primary forces at work: the internal influence or diffusion growth after the first year
in the modified model (representing influences from existing adopters) and the external influence or
the first-year adoption level in the modified model (representing all other influences) that drive an
adoption decision. This may explain why the explanatory variables influence these two diffusion
parameters differently from the survival model, where no such internal/external distinctions are
assumed. Second, the survival model uses two components: the baseline hazard and the influence of
the explanatory variables. The latter adjusts the baseline hazard rate to yield a better prediction for when a specific diffusion state is reached. As a result, some of the explanatory power of the model may reside in the baseline hazard component (similar to an intercept in linear regression), which all countries are subject to in the diffusion process.

CONCLUSION

We proposed a new state-based theory for the diffusion for the international diffusion of digital wireless phone technology. The theory argues that there should be a different set of dominant factors that influence diffusion speed across various states of the diffusion process. We conceptualized three critical diffusion states, based on Roger’s diffusion theory of innovation: the Introduction State, the Partial Diffusion State, and the Maturity State. On the basis of this theory, we tested the effects of country environmental factors, digital and analog wireless phone industry environmental factors, and technology policy factors. We focused on diffusion speed from the Introduction State to the Partial Diffusion State (15% penetration) using a modified Bass model and a coupled-hazard survival model. One of the significant findings across the two models is that multiple digital wireless standards significantly slow down diffusion. Instead, one standard appears to promote faster growth in the international diffusion of digital wireless phones. Also, our results indicate that higher digital wireless phone service prices slow down diffusion. Competition in the analog and digital wireless phone industry shape the growth of digital wireless phone diffusion. In addition, different standardization and licensing policies influence diffusion speed.

From a theoretical perspective, the primary contribution of our work lies in the state-based theory of diffusion. We believe that this theory contributes a new conceptualization about the diffusion process as consisting of multiple interdependent states to the adoption and diffusion research stream.
The state-to-state diffusion framework also allows researchers to empirically assess the existence and strength of the influence of explanatory variables and compare them across those diffusion states. In addition, we believe that our theoretical model considers a more comprehensive set of explanatory variables than previous diffusion studies.

Our findings have several managerial and policy implications. The results strongly suggest that one digital standard leads to faster diffusion growth. In order to promote faster diffusion growth of digital wireless phones, policy makers should promote open market competition where there are several operators compete for customers. In addition, regional licensing policy, where operators are allowed to compete in specified geographical areas, appears to be the optimal policy to promote diffusion growth in the long run.

REFERENCES


