

## NETWORK EFFECTS REVISITED: THE ROLE OF STRONG TIES IN TECHNOLOGY SELECTION

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**This paper extends the theory of network effects by moving beyond the traditional treatment of the installed base of a technology as composed of “*N*” identical users, each having the same effect on the rest of the users. Borrowing from social network theory, I propose the concept of strong-ties network effects as a key determinant of technology adoption in cases where several technologies compete. A discrete-choice model was tested in the wireless telecommunications industry.**

The concept of network effects or “externalities” has, since the mid 1980s, been the subject of increasing attention from academics and practitioners of management and economics. Proponents argue that network effects characterize many high-technology industries today and that they seem to challenge much of the thinking derived from previous experience and research in management (Katz & Shapiro, 1985; Shapiro & Varian, 1999). Despite the importance of the concept, most research insights about network effects still come from predictions based on theoretical models or from single-firm case studies and, to date, little rigorous empirical research has been done (Kauffman & Wang, 2002). Several authors have hypothesized that network effects have a major role in markets in which alternative and incompatible technologies compete for dominance. The literature on the topic has suggested that such markets tend toward a “winner takes all” outcome; network effects, it is argued, will ensure that the technology with the largest installed base—that is, with the largest number of users—will become increasingly attractive to existing users and will in turn attract new users, demonstrating a well-documented “bandwagon” effect. Even if the final outcome allows for more than one technology in a market, the installed base is singled out as a key determinant in users’ technology choice.

This paper sheds light on three main questions: How does the intensity of network ties affect technology choice? Can the existing conceptualization

of network effects be improved with empirical evidence? Once these conceptual issues are addressed, What is the relative importance of network effects vis à vis other factors that influence technology choice? These related theoretical and empirical questions are relevant. A networks perspective seems to have gained significant ground in management theory during the last decade, with insights coming from at least two separate and largely independent streams of literature: industrial economics and social network theory. An attempt to foster cross-pollination of these bodies of work is likely to bring new, valuable insights. Moreover, the issues addressed here have direct strategic implications for organizations that compete in industries influenced by network effects.

In this article, I extend the theory and empirical research on network effects by moving beyond the traditional treatment of a technology’s installed base as composed of a network of “*N*” identical users, each of them having the same effect on the rest of the users of the network. Existing theory implies that the addition of any one user to network  $Y_1$ , other things being equal, increases the value of network  $Y_1$  over that of competing network  $Y_2$  for all existing and potential users. Thus, the larger the total network, the larger the expected benefit for a user that chooses to join that particular network. I extend this theoretical implication by borrowing from social network theory in order to divide such a total network into two main parts: a part that has “strong ties” with a given user or potential user (Ahuja, 2000; Rindfleisch & Moorman, 2001), and the rest of the network.<sup>1</sup> The hypothesis here is that, for a given user, the strong-ties part of the

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<sup>1</sup> Note that the way I extend the theory by refining the definition of an existing theoretical “unit” (network effects) is presented in Dubin’s (1978) book, *Theory Building*, as an “invention by subdivision”—one of two main ways of improving upon an existing theory.

network will have greater influence than the total network on the decision of which technology to adopt. Fitting a discrete-choice model, I show that this is indeed the case for a sample of cellular operators choosing between three different second-generation wireless technologies. My results provide a finer level of granularity for the modeling and testing of network effects and have important implications for firm strategy—for instance, strategy related to building up early market share in an industry. The findings also extend current literature on technology diffusion, particularly that related to the importance of a critical mass in technology adoption (Rogers, 2003). In addition, this research setting allows me to show that, although most of the existing literature on the topic focuses on end users, network effects can also exist upstream in a “value system.”

### THEORY AND HYPOTHESES

Researchers in industrial economics introduced the concept of network externalities to describe a situation in which “the utility that a user derives from consumption of the good increases with the number of other agents consuming the good” (Katz & Shapiro, 1985: 424). The “number of other agents consuming the good,” often referred to as total network size, is defined in a straightforward way: “The network size is simply the total number of consumers owning units of hardware that are compatible with the individual’s unit” (Katz & Shapiro, 1992: 59). Katz and Shapiro also distinguished between direct and indirect network externalities. The former are the direct physical effects generated by the addition of physical connections (users) to a network, and the latter, indirect network externalities, capture the indirect effects of network size and give rise to consumption externalities. The distinction between direct and indirect network effects is widely accepted, and it has often been represented by the examples of hardware and software, each the other’s complementary product (Church & Gandal, 1992; Gupta, Jain, & Sawhney, 1999). In this body of research, the larger the total network size and the greater the availability of complementary products for a technology, the greater the attractiveness of that technology to current and potential users.

Most existing empirical studies have explored the importance of network effects on technology adoption (Brynjolfsson & Kemerer, 1996; Tam & Hui, 2001; Wade, 1995; Schilling, 2002). In keeping with industrial economics theory, these studies have considered total network size as a measure of the strength of network effects, irrespective of the

characteristics or physical location of the user base. For a given technology, a given new user added to the “*N*” affects the utility derived by the rest of the users in the same form and at the same magnitude as any other user that could have entered in her or his place (Farrell & Saloner, 1986; Katz & Shapiro, 1985). In other words, all users make the same contribution to the utility of other members of the user base—irrespective of their location in the network.

This existing conceptualization of network effects, however, does not seem to fully explain observable market outcomes, particularly when it comes to technology adoption situations. If consumers based their purchase decisions on the total network size of each particular technology, then one could not explain the prevalence of pockets of use of technologies that have long since lost the battle for overall market share to rivals. For instance, Apple has been the personal computer of choice in the publishing and media industries for many years, despite the overwhelming overall market share advantage the “Wintel” camp has held since the mid 1990s. Similarly, in videogames, where several competing formats exist, anecdotal evidence suggests that children tend to prefer the system that predominates in their specific peer group (school classmates), irrespective of whether that system has the largest overall network. Studies of technology diffusion have addressed similar phenomena and found a similar pattern; for instance, a study of family planning methods in Korea showed that whole villages tended to adopt one specific method, irrespective of that method’s nationwide rate of adoption (Rogers, 2003). In such cases, contrary to what theory predicts, specific groups of consumers may select a technology that has a lower overall installed base than its competing alternatives.

One obvious explanation for this apparent deviation from theoretical predictions is that other factors are at play, besides network effects. Consumers could be basing their choices on, say, the price or technological characteristics of each competing system (Shapiro & Varian, 1999; Suarez, 2004), paying less attention to each system’s overall installed base. But even after considering these factors, one cannot satisfactorily explain the anomalies. First, the “other factors” do not always move in the direction that would explain consumers’ preference for a system that has a smaller installed base. In the example above, Apple’s PC prices have been significantly higher than that of competing systems and, with the launching of Windows in 1985 and subsequent improvements, Microsoft seriously eroded Apple’s initial technological advantage. Second, if

factors other than network effects explained why some customers opt for a system despite its smaller installed base, one would expect to see these customers randomly distributed, not clustered in identifiable groups, as in the Korean village example above.

A fresh look at the concept of network effects can shed light on these issues. Social network theory has long studied the effect of different types of network structure on organizational outcomes and decisions. The strength-of-ties perspective (e.g., Rindfleisch & Moorman, 2001) suggests that, for any particular actor, specific parts of a network—those parts with particular tie characteristics—are more relevant than others. A basic postulate of social network theory is that there are different densities in different parts of a network and that relationships among the different actors in a network can be broadly classified into some basic types: strong versus weak ties and direct versus indirect ties (Ahuja, 2000). Strength of ties is typically measured as a function of frequency of contact, although it may also comprise reciprocal obligations, emotional intensity, and intimacy (Granovetter, 1973). Two opposite perspectives can be found in the literature. Granovetter (1973; cf. Rogers, 2003) emphasized the importance of weak ties, postulating that large networks with many weak ties improve an organization's performance by granting it access to more diverse information from a larger environment. Other researchers have emphasized the importance of strong ties (e.g., Kraatz, 1998; Uzzi, 1997), suggesting that small networks characterized by strong ties provide the necessary loyalty and coordination for improved organizational performance.

Although they have evolved separately, a parallel exists between the strength-of-weak-ties perspective in social network theory and the theory of network effects from industrial economics, in that both emphasize total network size as a key determinant of organizational performance, and both implicitly or explicitly address arm's-length relationships among network actors (Uzzi, 1997). For a given organization, the larger its total network, the more positive the outcome. However, a situation in which organizations have to choose among two or more new technologies that compete for market dominance is often characterized by high uncertainty and rapid environmental change. Research on the strength of strong ties has pointed out that a small network with strong ties will be particularly valuable "in facilitating organizations' attempts to adapt their core features in response to environmental change" (Kraatz, 1998: 623). Similarly, Cook (1977) argued that organizations seek to re-

duce uncertainty by trying to create negotiated and more predictable environments. That is, under environmental uncertainty, a small network of strong ties should prove valuable. I therefore hypothesize:

*Hypothesis 1. The probability that a user chooses a given technology over competing alternatives is positively associated with the relative network size of that technology in a specific part of the total network where the user has strong ties.*

Even if Hypothesis 1 were known to be true, the effect of the overall network (weak ties) on technology selection cannot be a priori assumed away. Empirical research in social network theory looking at strength-of-ties issues typically tests for the effects of both weak and strong ties, suggesting that the relative importance of each type of tie varies with the type of environment and the complexity of the information being considered (e.g., Collins & Clark, 2003). Most of the existing studies seem to agree that the more uncertain the environment and the more complex the information, the greater the value of strong ties relative to weak ties (Hansen, 1999). Therefore, I expected strong-tie network effects to dominate over classical network effects:

*Hypothesis 2. Strong-ties network effects are stronger than classical network effects as a predictor of the probability that a user chooses a given technology over competing alternatives.*

## METHODS

### Research Setting

This study's data relate to the deployment of second-generation wireless technologies in North America, South America, and Central America, a large region that I refer to as the Americas. Countries in this region were selected because their free market approach to second-generation wireless technologies allowed these alternative technologies to compete for market share and eventual dominance: every operator wanting to provide a service in any country in the Americas had to choose which technology to use before starting operations. Three alternative and incompatible second-generation technologies were available to cellular operators: the global system for mobile communications (GSM), time-division multiple access (TDMA), and code-division multiple access (CDMA). GSM and TDMA are based on a similar time-division technology, in which users are allocated unique time slots within each channel: every cellular handset in the system is assigned a specific time position on the radio channel, thus effectively sharing the

channel and increasing network capacity. CDMA, the newest of the three technologies, assigns unique codes to each communication to differentiate it from others in the same spectrum, thus achieving greater capacity than GSM and TDMA.

My research setting is novel in that, to date, most studies of network effects have focused, implicitly or explicitly, on end customers (Brynjolfsson & Kemerer, 1996; Gruber & Verboven, 2001; Katz & Shapiro, 1985) who seem to be aware of the competing technologies used in products such as VCRs and PCs and actively choose among them. In contrast, wireless users tend not to be aware of the underlying technology (GSM, TDMA, or CDMA) running on their phones. One reason for this absence of awareness may be that end users can seamlessly call both users of their own networks and users of other networks within a primary coverage area. Thus, network effects do not appear to exist at the end user level in wireless. However, a closer look suggests that network effects do in fact exist, but they are primarily at the operator rather than at the end user level. In each country or state where it wants to operate, a network operator must obtain a license for a piece of the spectrum; once granted a license, the operator works under a well-defined local regulatory regime. A given operator entering the industry in a country during the period of my data collection had to decide, prior to starting operations, which of the available technologies to use for its network. Given the fact that each piece of equipment was designed for a particular technology, the technology decision was important: the sizes of the necessary investments made posterior switches to different technologies very unlikely, and operators saw their technology decisions as irreversible.

For several technical reasons, network effects also played a role in operators' technology decisions. Firstly, it was only possible for operators to provide their users with "roaming" communication (the use of a phone outside its primary coverage area) with users of other networks having the same basic technology. Prohibitive price and component size considerations ruled out multitechnology handsets prior to the early 2000s. Secondly, despite the fact that users of one network could call users of other networks with different technologies seamlessly when operating within their primary coverage areas, basic compatibility across technologies and networks was limited to voice. When other services started to unfold, such as text messaging, they initially could not cross technologies. Thirdly, the availability and cost of technical support was an important consideration in an operator's technology decision, particularly those who owned or

planned to have multiple licenses and those located in small, remote countries.

During the period 1992 through 2001, a total of 177 operators initiated services in the 47 countries considered in this study. Of these, 57 operators chose CDMA at entry, 21 chose GSM, and 99 chose TDMA. Owing to lagged variables and some missing data, the effective sample decreased to 95 operators. There was no evidence of sample selection bias, as suggested by two-sample tests (results not reported here) and by the fact that technology choices in the sample seemed to follow quite closely those of the total population.

Quarterly data for operators came from the World Networks, Forecasts & Tariffs Datapack, July 2001 edition, and the EMC's World Cellular Database, for the period extending from the third quarter of 1992 through the second quarter of 2001. Data were available on the following: the technology used by an operator (TDMA, CDMA, or GSM); the spectral frequency allocated to each operator; the starting date of operations; operation status; and network equipment supplier. In addition, the EMC database provided data by manufacturer on new handset models introduced in the market for each technology. I conducted several interviews with players in the industry in order to gain a deeper understanding of the industry and its dynamics.

I considered the window of decision making for each operator in the sample, capturing each explanatory and control variable two quarters prior to its actual entry time—that is, at the time when the operator had to make the largely irreversible, up-front choice of technology. My model therefore uses a "two-lag specification" for all independent variables, as the final decision to go for a particular technology typically takes place at least six months before market entry. (I tested up to four lags in analyses not reported here; the main results did not change.)

### Dependent and Explanatory Variables

**Technology choice.** This study's dependent variable registers each operator's choice of technology. For a given operator, technology choice takes a value of 1 if CDMA was chosen, 2 if GSM was chosen, and 3 in the case of TDMA. In practice, for two main reasons, not all technologies were available to every entering operator at any given time. First of all, the three technologies did not become available simultaneously: CDMA only became commercially available in 1995, whereas TDMA was available in 1993, and GSM was present as early as 1991. Secondly, the technicalities associated with specific spectrum frequencies could

make it difficult for technologies to operate, de facto ruling out some options for some operators. Table 1 summarizes the different combinations of technology and allocated frequencies used by various operations worldwide, up to 2002, and shows that some frequencies did not work with particular technologies (for instance, GSM was never implemented in the 800 megahertz [MHz] frequency). In the present study, I followed the most stringent compatibility test: if a technology was never implemented worldwide in a particular frequency (a 0% in Table 1), I removed that technology as an option for all operators entering the market in a country or area where its government had allocated that frequency to second generation wireless service. In general, in any given quarterly period, the model only addresses the technology options available to each entering operator at that time, and cases in which only one option was available are eliminated.

**Strong-ties network.** The proposed explanatory variable was built as follows: each entering operator was associated with the country where it operated; and for every country A, I determined three top international calling partners, B, C, and D. The number of minutes of outgoing publicly switched telecommunications traffic, as reported in the *Tele-Geography Annual Traffic Report 2001*, was the criterion. The assumption that countries B, C, and D would be the most important roaming destinations for users from country A was confirmed during my interviews with industry players (roaming data per operator, arguably the best measure of strength of ties, was not available for the data collection period). From the EMC database I then computed, for each of a country's three top calling partners, the total number of subscribers using a

particular technology divided by the total number of active subscribers in the partner country in any given quarterly period. Finally, I calculated the variable measuring the effects of a *strong-ties network* as the simple average of the scores of B, C, and D. I also tried a weighted average specification in which the weights were the traffic volumes between country A and its top three calling partners; the results did not change substantially.

### Control Variables

The control variables used for this study are detailed below.<sup>2</sup>

**World network.** I measured the size of the worldwide network for each technology ("classical" network effects) by taking the total number of operators worldwide using a particular technology and dividing by the total number of active operators in any given quarterly period. This variable is calculated quarterly for each of the three technologies.<sup>3</sup> These data were compiled from the EMC database.

**Local network.** In large countries—where each operator tends to serve only part of the country—previous technology decisions by other local players may be important for an entering operator. I thus computed a local network variable: for each operator entering country A, I divided the total number of country A operators that were already using a particular technology by the total number of active operators in that country in any given quarterly period. (Data came from the EMC database.)

**Complementary products.** For each technology in any given quarter, I calculated the total number of new, compatible handset models introduced

**TABLE 1**  
Deployment of Wireless Communication Technologies by Frequency<sup>a</sup>

Frequency	CDMA	GSM	TDMA	Grand Total
800	39.1%	0.0%	53.8%	11.1%
900	0.0	51.9	0.0	39.3
1700	13.7	0.0	0.0	1.8
1800	0.0	14.1	0.0	10.7
1900	18.6	2.5	2.5	4.6
800/1900	28.6	0.0	43.8	8.6
900/1800	0.0	31.5	0.0	23.9
Grand total	100.0%	100.0%	100.0%	100.0%

<sup>a</sup> World figures up to 2002, from the EMC database. CDMA is code-division multiple access; GSM is the global system for multiple communication; and TDMA is time-division multiple access.

<sup>2</sup> Apart from the variables listed here, in unreported analyses I also entered variables derived from previous research to control for other factors that might influence users' technology choice when several technologies compete for dominance. These were as follows: complementary products (Cusumano & Gawer, 2002; Gupta et al., 1999; Katz & Shapiro, 1985); technological performance (Christensen, Suarez, & Utterback, 1998; Suarez & Utterback, 1995); vendor credibility (Tam & Hui, 2001); entry timing advantages (Mitchell, 1989); price (Shapiro & Varian, 1999); and firm's prior history (Klepper & Simons, 2000). I did not consider cohort or age effects, or firm's prior history.

<sup>3</sup> Note that computation of this variable and the following one, local network, could alternatively be based on end subscribers. Indeed, subscriber-based and operator-based measures are highly correlated and yield basically the same results for my purposes here.

during the previous year. Handsets are the most immediate complementary product to a particular wireless technology and are typically supplied by independent firms. I considered a four-quarter window, given the rapid obsolescence that characterizes the handset market: new handsets, not old ones, tend to attract users and drive adoption. Handset information data were again from the EMC database.

**Technological superiority.** I considered each technology's spectral efficiency—that is, a technology's ability to make efficient use of its allocated frequencies. Two main elements are considered in calculating a system's spectral efficiency: first, the number of users that an individual radio frequency channel can support; second, the frequency reuse factor, which is the extent to which a given frequency can be reused at adjacent cell sectors. Voice capacity per MHz of spectrum was then defined as the number of users supported per cell sector by 5 MHz of spectrum. Data for spectral efficiency came from Deutsche Bank and from industry associations.

**Vendor (brand) credibility.** Operators buy their networks from network equipment manufacturers that often sell more than one technology but tend to specialize and claim particular expertise in one. I captured this vendor credibility or brand effect as the proportion of the total number of technology systems of a particular type that had been sold and deployed by a particular vendor, up to a given quarter.

**Price.** I considered the required investment for each technology per subscriber, obtaining estimates from the 1998 Pyramid Research Wireless Market and Strategy Studies, a project of the *Economist Intelligence Unit*. In calculating these prices, Pyramid only includes the investment costs for cellular switching, radio base stations, and operational software. Towers, poles, and cell site housing or site expenses (such as leasing costs and rights of way) are not included, but one can assume that these omitted costs vary randomly across technologies. Pyramid's pricing estimates were global and were available throughout the period of this study from the time each technology became commercially available.

**Entry timing.** I built an entry timing variable to explore possible early entry advantages in each market. The first technology to become available in a country received a value of 0. I then computed, for each of the remaining two technologies, the number of quarters that had elapsed until it became available.

## Analysis

I used a random utility model to describe unordered choices; specifically, I fitted a conditional "logit" regression. Operators choose among different technologies and derive a certain utility from their choice based on choice-specific attributes,  $x_{ij}$ . Generally, for the  $i$ th operator faced with  $j$  technology choices:

$$U_{ij} = \beta' x_{ij} + \epsilon_{ij}.$$

For operator  $i$  one can define  $Y_1$  as a random variable that indicates the choice made—i.e.,  $Y_1 = 1, 2,$  or  $3$ —for each of the three available technologies: CDMA (1), GSM (2), or TDMA (3). Following McFadden (1974), under certain assumptions one can reduce the model to:

$$\text{Prob}(Y_i = j) = \frac{\exp(\beta' x_{ij})}{\sum_{j=1}^3 \exp(\beta' x_{ij})}.$$

In this equation it is assumed that the vector of error terms follows a logistic distribution allowing use of a discrete-choice model. The command CLOGIT in STATA 8.2 was used to estimate the modes, as is shown in Table 3a, and the command DISCRETECHOICE (option EFFECT) in NLOGIT 3.0 was used to estimate the elasticities reported in Table 3b.

Elasticities for the probability of choice  $j$  with respect to changes in attribute  $m$  of choice  $k$  were calculated on the basis of the following formula reported in Greene (2003):

$$\frac{d \ln P_j}{d \ln x_{km}} = x_{km} [1(j = k) - P_k] \beta_k.$$

The subscripts  $i$  were dropped for simplicity, and  $1(A)$  is an indicator function equal to 1 if  $A$  is true, 0 otherwise.<sup>4</sup>

## RESULTS

Table 2 provides a correlation matrix and summary statistics for the all the variables included in my models.<sup>5</sup> Table 3 reports the parameter estimates for the conditional logit models and helps with assessment of the significance of the different variables and the validity of my hypotheses. Model 1 in Table 3a, which contains all the independent

<sup>4</sup> For a detailed example of a conditional logit model, please see Greene (2003), pages 729–735.

<sup>5</sup> Had I used a linear model, some of the correlations in Table 2 could have represented a problem.

**TABLE 2**  
**Descriptive Statistics and Correlations among Variables by Technology<sup>a</sup>**

Variable <sup>b</sup>	Mean	s.d.	1	2	3	4	5	6	7
CDMA									
1. Strong-ties network	0.27	0.15							
2. World network	0.08	0.04	0.71*						
3. Local network	0.27	0.34	0.49*	0.50*					
4. Complementary products	31.00	14.00	0.71*	0.93*	0.46*				
5. Technological superiority	5.30	0.00							
6. Vendor credibility <sup>c</sup>	0.23	0.17	0.55*	0.40*	0.24	0.39*			
7. Price	389.24	75.18	-0.86*	-0.88*	-0.44*	-0.86*		-0.52*	
8. Entry timing	2.81	3.52	0.33*	0.56*	0.52*	0.47*		0.02	-0.50*
GSM									
1. Strong-ties network	0.31	0.25							
2. World network	0.74	0.10	0.71						
3. Local network	0.13	0.21	-0.12	0.13					
4. Complementary products	93.16	49.42	-0.68	-0.98*	-0.15				
5. Technological superiority	2.50	0.00							
6. Vendor credibility <sup>c</sup>	0.21	0.15	0.41	0.35	0.21	-0.18			
7. Price	349.95	47.51	0.77	0.98*	0.19	-0.97*		0.30	
8. Entry timing	2.83	3.13	-0.48	-0.33	0.57	0.31		0.03	-0.41
TDMA									
1. Strong-ties network	0.73	0.14							
2. World network	0.17	0.02	-0.26						
3. Local network	0.72	0.40	0.27*	0.03					
4. Complementary products	8.71	4.83	-0.06	0.77*	-0.12				
5. Technological superiority	3.00	0.00							
6. Vendor credibility <sup>c</sup>	0.42	0.12	-0.01	0.17	0.07	0.05			
7. Price	338.85	25.34	0.26	-0.69*	-0.31*	-0.36*		-0.36*	
8. Entry timing	7.12	4.50	0.13	0.37*	0.80*	0.14		0.11	-0.56*

<sup>a</sup> For CDMA (code-division multiple access),  $n = 29$ ; for GSM (global system for multiple communication),  $n = 6$ ; for TDMA (time-division multiple access),  $n = 52$ .

<sup>b</sup> Spectral efficiency is constant per technology through time.

<sup>c</sup> Brand credibility.

\* $p < .05$

variables, shows a significance pattern that remains stable through the different models (note that the parameters for each variable do not change much between model 1 and model 3). I used model 3, the most parsimonious model, to calculate the predicted probabilities and elasticity of probabilities in Table 3b.

Hypothesis 1 receives strong support from the analysis, as the coefficient for the strong-ties network variable remains significant at the .01 level across all models. Note also that the data do not support the role of classical network externalities, as the coefficient for the variable "world network" does not achieve significance. Thus, it follows that Hypothesis 2 is also supported: the strong-ties network effect is stronger than the classical network effect here. In other words, when choosing which technology to purchase, cellular operators tend to pay more attention to decisions made previously by

other operators in a selected subset of countries with which they have strong ties than to the overall situation in the world.

Three control variables also achieve significance in this analysis. The importance of complementors in the operators' decisions receives mild support, as the coefficient for this variable achieves significance at the .05 level in model 2 and borderline significance in model 3; this variable was indeed the only one that changed in level of significance across the models. My findings here are consistent with the literature on the role of complementors in different industries (Cusumano & Gawer, 2002; Wade, 1995) and also with anecdotal evidence in this industry: much of the blame for the slow growth of third-generation networks in Europe in 2003 and 2004 has been attributed to poor availability of handsets for the new technology. Two other variables, technological superiority (Suarez &

**TABLE 3**  
**Results of the Logit and Probability Analyses**

**(3a) Parameter Estimates of Conditional Logit Regression Models<sup>a</sup>**

Variable	Model 1	Model 2	Model 3
Strong-ties network	4.68** (1.64)	4.98** (1.72)	4.47** (1.51)
World network	2.35 (2.21)		
Local network	1.93 (1.09)		
Complementary products	0.01 (0.01)	0.02* (0.01)	0.02 (0.01)
Technological superiority	0.97* (0.40)	0.91** (0.33)	1.05** (0.28)
Vendor credibility	9.40** (1.83)	8.92** (1.67)	8.72** (1.65)
Price	0.02 (0.01)	0.01 (0.01)	
Entry timing	-0.09 (0.12)	0.06 (0.08)	
<i>n</i>	95	95	95
Pseudo- <i>R</i> <sup>2</sup>	0.59	0.56	0.54
Likelihood-ratio $\chi^2$	90.70	86.73	83.28

**(3b) Predicted Probabilities and Their Frequency and Elasticity**

Variable	CDMA	GSM	TDMA
<b>Probabilities and frequencies</b>			
Probability	0.39	0.03	0.58
Predicted <i>n</i>	37	3	55
Actual <i>n</i> : Estimation sample	37	6	52
Actual <i>n</i> : Total sample	57	21	99
<b>Elasticity</b>			
Changes with respect to strong-ties network			
CDMA	0.71	-0.45	-0.45
GSM	-1.38	1.24	-1.38
TDMA	-0.06	-0.06	0.64
Changes with respect to complementary products			
CDMA	0.30	-0.19	-0.19
GSM	-0.33	0.29	-0.33
TDMA	-0.01	-0.01	0.06
Changes with respect to vendor creditibility			
CDMA	1.85	-1.17	-1.17
GSM	-3.93	3.51	-3.93
TDMA	-0.15	-0.15	1.58
Changes with respect to technological superiority			
CDMA	3.41	-2.15	-2.15
GSM	-1.58	1.41	-1.58
TDMA	-0.08	-0.08	0.85

<sup>a</sup> Estimated coefficients are shown, with standard errors in parentheses.

\*  $p < .05$

\*\*  $p < .01$

Utterback, 1995) and vendor credibility (Tam & Hui, 2001), consistently achieve the .01 significance level throughout the models.<sup>6</sup> Model 3 shows a good fit (model  $\chi^2 = 83.28$ ; pseudo- $R^2 = .54$ ) that

<sup>6</sup> The fact that my model captures the effects of vendor credibility and technology installed base may explain why the entry-timing variable turned out not significant: establishing credibility and building up an early installed base are often mentioned as key aspects of early entry advantages. Indeed, the entry-timing variable does become significant ( $p$  of .005) when vendor credibility and installed base effects are removed from the model.

can also be seen in the model's predictive power in Table 3b, which gives predicted probabilities and observed frequencies. Note that the model slightly overestimates the probability of choosing TDMA, at the expense of GSM, but is otherwise very sensitive to and closely matches the actual structure shown by the data set. In addition, it has parsimony, as a good fit is achieved with few predictors.

The results of Table 3a relate to the beta parameters in the operator's utility function specified above; I now turn to interpreting the effect of the predictors. Parameter estimates for predictors in a choice model such as this are not directly related to

marginal effects (Greene, 2003; Hensher & Truong, 1985). Therefore, in order to understand the effect of the significant explanatory variables on technology choice, I needed to calculate the elasticity of the probabilities, as defined above; these are reported in Table 3b. The table shows the change in the probability of choosing a particular technology relative to changes in a particular explanatory variable. I first report the elasticity of the probabilities with respect to the strong-ties network variable. The numbers show that the effect of a network comprised of strong ties on technology choice varies with technology; for instance, a 1 percent increase in GSM's average share among operators in the strong-ties countries relevant for a particular operator increased the probability of that operator choosing GSM by 1.2 percent. The same percent increase in the case of CDMA brings about a 0.7 percent change in the probability of an operator choosing CDMA, while a 1 percent increase in TDMA share in the strong-ties countries brings a 0.6 percent increase in the probability of an operator choosing that technology.

The remainder of Table 3b reports the elasticity of the probabilities for the other significant predictors in the model and can be interpreted in the same way as above. For instance, a 1 percent increase in the availability of complementors for GSM brings an increase of around 0.29 percent in the probability of an operator choosing GSM. Similarly, a 1 percent increase in the availability of complementors for CDMA or TDMA brings an increase in the probability that these technologies will be selected of 0.3 and 0.06 percent, respectively.

## DISCUSSION

Theoretical models in industrial economics rely on the assumption that networks are composed of identical users each having equal effect on and equal importance for the rest of the users. According to this view, each new user in a network adds an equivalent amount to the utility derived by all the other users in that network—that is, the magnitude of a network effect is directly related to the number of total users in the network. My study shows that, by considering the relative importance of specific segments of a network for the particular agent that is making a technology decision, this basic conceptualization can be improved. Research in social network theory suggests that networks are not uniform and can be classified in accordance with their strength of ties. The notion of the strength of strong ties is that small networks characterized by strong ties tend to be more valuable for organizations than large networks with weak ties,

particularly under conditions of environmental change and uncertainty. The current results confirm the latter proposition since, according to my data, the technology decisions of entering cellular operators are influenced not by the total installed base of each technology, but rather by the installed base in a selected list of places where the entering operator expects to have the strongest ties.

These findings have interesting implications for existing theory. Scholars in economics and management have largely accepted the notion of “excess inertia,” which is a bias toward the system with the largest installed base, when network externalities are present (Farrell & Saloner, 1986). When two or more incompatible technologies compete, excess inertia leads to “tipping markets” in which one technology ends up dominating all spaces in a product category. This notion is related to that of the critical mass of adopters in the technology diffusion literature. A critical mass occurs at the point at which enough adopters have chosen a particular technology that the technology's further rate of adoption becomes self-sustaining (Rogers, 2003). Some exceptions to this self-fulfilling excess inertia outcome have been proposed, but the typical assumption has been that the system with a lower installed base enjoys a significant advantage—for instance, newer and superior technological capabilities (Katz & Shapiro, 1992). My results suggest that, even in the absence of clear technological superiority, the forces of excess inertia may not apply uniformly throughout a market. If customers' system decisions are based not on the overall installed base, but on the base in a specific part of the network with which they have strong ties, then the notions of excess inertia and critical mass should be reconsidered when it comes to technology selection. In particular, markets may not necessarily tip totally in favor of one alternative. As customers choose the system that prevails in their strong ties networks, a situation of “multiple equilibria” (where more than one outcome is possible) can result. The wireless industry analyzed in this article is such a case: each of the three competing technologies was able to hold on to different parts of the market not necessarily on the grounds of geography, but on the basis of the strength of each operator's ties.

This study raises several questions of theoretical and managerial importance that further research could address. There are marketing strategy implications for firms competing in technology standard battles. If groups of customers base their technology decisions not on the overall installed base but on the situation of specific parts within their network, then a better understanding of the type and strength

of ties that predominate in a given network may lead, for instance, to a more targeted (and arguably more effective) marketing effort—for instance, the “viral marketing” advocated by marketing diffusion scholars. Another line of inquiry may therefore be to explore the nature of the ties that are more relevant to network effects in different situations. I have focused here on economic ties between network operators that arise from their users’ long-distance calling patterns, but other type of ties (e.g., religious, professional) may be more relevant for technology decisions in other situations. Further research in different industries is also needed to study the relationship between strong-ties network effects and classical network effects. Three hypothetical scenarios can be considered a priori. First, an industry that features very strong ties could simply annul classical network effects, as in the wireless industry case here. Second, an industry with moderately strong ties may allow for both strong ties and classical network effects to be significant. Finally, an industry in which weak ties predominate would de facto revert to the classical case, a monolith that cannot be broken into parts on the basis of tie strength. Which of these scenarios prevails in a particular case has important implications for firm strategy: the use of firm resources to build overall market share, for instance, seems to be more effective in the last scenario than in the previous two.

An additional area for future research relates to the role of network effects at different stages of a value system. Most theoretical models address network effects at the end user level, where individual customers decide which technology or network to join (Farrell & Saloner, 1986; Katz & Shapiro, 1992). This focus implies that end users are aware of the different technologies in competition and their main advantages and disadvantages. Although this may be a reasonable assumption in most contexts, it is certainly not always the case. The current study shows that, despite weak or nonexistent network effects at the end user level, network effects can be found upstream in an industry—in the case explored here, at the wireless operator level. If the strength of network effects varies with the different stages of an industry value chain, it follows that some technologies could be locked out (Schilling, 2002) of an industry in its upstream stages, before end customer dynamics kick off. This formulation opens an interesting area for empirical and theoretical research related to firm strategic maneuvering along the value system.

Overall, this study shows that researchers’ existing understanding of network effects and their strategic implications, which comes mainly from in-

dustrial economics, can be improved by cross-fertilization with related research streams that have studied similar network phenomena. I have considered only one aspect of social network theory here, namely, the strength-of-ties perspective. Further research could try to integrate other aspects of network theory into the analysis—for instance, a network’s topology. There is a fresh and growing empirical literature on network theory that could shed additional light on network effects, standards formation, and technology choice by organizations (e.g., Venkatraman, Lee, & Iyer, 2004). Such data-based studies can potentially bring a new set of answers to questions about the complex competitive dynamics that characterize industries ruled by network effects.

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