

The Role of Within-Brand and Cross-Brand Communications in Competitive Growth

Consumer-generated communication processes have drawn increasing attention of marketers and researchers. However, an underresearched issue is that interpersonal communications are not always brand specific. Thus, a person can adopt a brand either as a result of communication with adopters of that brand (within-brand influence) or as a result of an interaction with adopters of competing brands (cross-brand influence). This study shows that the interplay between within- and cross-brand influence can have a substantial effect on the growth of markets under competition. The authors develop a model that explicitly represents these two influences and focus on the case of two otherwise identical competing brands with different entry times. As a result of within-brand influence, current customers create an interaction-based advantage for the first entrant, which grows with time. Thus, we illustrate how customers should be viewed as market assets who yield increasing returns during the diffusion process. Conversely, cross-brand influence enables a market follower to enjoy a shorter takeoff time. Given the combination of both, the authors predict the “dual pattern,” characterized by a fast takeoff for a follower, followed by a widening gap in favor of the first entrant, all else being equal. They show that such a pattern dominated the market growth of the cellular industry in Western Europe. They explain the reasons behind this dual pattern, rule out straightforward alternative explanations, and discuss the managerial implications.

Keywords: word of mouth, brand management, diffusion of innovations, cellular/mobile, telecommunications, pioneering advantage

A major product introduction in the United States in 2007 was Apple’s launch of the iPhone. Close observation of the introduction yields two key inferences: First, the promotion of iPhone was heavily tilted toward word-of-mouth communications and buzz instead of paid advertising (Reuters 2007; Word-of-Mouth Marketing Association [WOMMA] 2007). Second, following Apple’s launch, several leading handset manufacturers, such as Samsung and Nokia, began launching smart phones with similar features (Yoon 2007). The market’s internal communication dynamics in this case might lead a person to wonder about the extent to which communication is specifically related to iPhone and, thus, the extent to which competitors

are enjoying the buzz generated by iPhone. While Apple is working under the assumption that interpersonal communication will help push its own product, allowing it a relatively low investment in advertising, others in the industry are enjoying the benefits of this cross-brand effect: To quote Verizon spokesperson Michael Murphy, “I would have to think that a rising tide lifts all ships” (Reuters 2007).

Although consumer-based communication processes are occupying increasing interest from academics and practitioners (Rosen 2000; WOMMA 2006), a notable but often overlooked issue is that the terms “word of mouth” and, more generally, “interpersonal communications” are not always brand specific. Potential adopters can communicate with the customers of a specific brand but eventually purchase a competing brand as a result of factors such as brand equity, price, availability, special offers, and a better match to their needs.

In line with this distinction, a firm may identify two sources of communications influence that constitute the focus of this study: “within-brand influence,” which originates with the firm’s own customers, and “cross-brand influence,” which originates with the customers of the firm’s competitors. The latter describes communications disseminated by competitors’ customers that eventually translate into the purchase of the focal brand. The distinction between within-brand and cross-brand influence has not been explored in the market growth literature. The Bass model and its extensions, which have been the main thrust of academic market growth modeling, have mostly focused on the category level (Mahajan, Muller, and Bass 1990;

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Mahajan, Muller, and Wind 2000). Although some efforts have been invested in modeling diffusion at the brand level (Krishnan, Bass, and Kumar 2000; Parker and Gatignon 1994; Peterson and Mahajan 1978; Shankar, Carpenter, and Krishnamurthi 1998), the interplay between communications effects that stems from the brand's own customers versus that of the competitors' customers has not yet been probed. In this study, we present a brand-level growth model that explicitly accounts for both within-brand and cross-brand influences and their effect on growth of competitive markets. Our main findings include the following:

- The rapid takeoff of the follower:* For similar brands entering in different periods, a later entrant often enjoys a faster and sharper takeoff than the first entrant. The reason is that the follower benefits from the cross-brand influence of the first entrant's customers, an advantage that the first entrant did not have in its early days as a monopoly. This finding lends a brand-level perspective to the new product takeoff literature, which in general has focused on the category level (Golder and Tellis 1997; Tellis, Stremersch, and Yin 2003). We show that in addition to the economical and cultural factors investigated so far, brand-level takeoff depends on competitive position and communication dynamics in the market.
- The "interaction-based advantage" of the first entrant:* As a result of within-brand influence, the customers acquired by the first entrant become a source of a self-reinforcing competitive advantage. Because, when competition enters, the first entrant has more customers than a later entrant, it can expect more brand-specific interactions and, thus, more new customers per period, who in turn generate more communications. We show that for similar brands, this becomes an "increasing return" process that widens the gap between the first entrant and a follower. We label this source of pioneering advantage as an "interaction-based advantage." Given these forces, the interplay between within-brand and cross-brand communications generates a dual pattern of growth—that is, a faster takeoff of the follower but an increasing advantage to the first entrant, all else being equal. We show how the exact nature of this dual pattern depends on the relative strength of within- and cross-brand dynamics.
- No need for perceptual difference:* The focus on similar brands is central to our analysis because it distinguishes the interaction-based advantage from previously identified sources of pioneering advantage and disadvantage that had been attributed to some perceived brand difference. In contrast, we show that even without any difference in perceived value among the brands, the within- and cross-brand influences will produce a differential growth pattern based on entry time. In this sense, the dual pattern is a fundamental aspect of the growth process that affects competitive growth regardless of specific brand-related idiosyncrasy. However, note that brands entering at different points might not be perceived as similar, in which case the interaction-based advantage will be just one of the factors that eventually create the differential sales pattern. We still find that for the later entrant to eventually overcome the interaction-based advantage of the pioneer, its growth parameters must be considerably larger than that of the pioneer (twice as large on average in our simulations).
- Dual pattern prevalence in cellular markets:* To investigate the dual pattern empirically, markets with relatively similar brands would help control for effects stemming from brand difference. We examined the cellular phone markets in Western Europe, in which regulatory effects created a relatively similar brand environment. Indeed, we identified the dual

pattern in 14 of 16 Western European countries. We use these brand-level data to show that the ratio of within- to cross-brand influence explains the dual pattern better than other, more straightforward alternatives, such as differences in price, churn, and technology.

We organize the rest of the article as follows: Next, we present the brand-level growth model and then demonstrate analytically the dual pattern. Then, we examine the dual pattern in the case of the Western European cellular market and show how the growth pattern in various countries can be explained by both within-brand and cross-brand dynamics. We then explore and question several alternative explanations for the dual pattern and conclude with the implications of our findings.

Cross-Brand and Within-Brand Influence

The premise of this article is that the growth of a competitive brand can be affected by the interplay between sources of information for prospective adopters: the brand's own users, who provide a within-brand effect, and the competitor's users, who provide a cross-brand effect. Our focus is on describing the aggregate influence of these effects rather than the communication processes and decision making on the part of the individual consumer. However, before we model the aggregate outcome of these effects, we briefly discuss the possible mechanisms that can generate these two types of influence.

An examination of the communication processes between adopters of a brand and prospective adopters suggests that they can be classified into brand-level and category-level communications. The term "communication" may include word of mouth as well as other nonverbal imitation processes that are part of the contagion process associated with new products (Van den Bulte and Lilien 2001). However, utility-related contagion, such as network externalities, is not considered under communication; we discuss this in greater detail subsequently.

Brand-level communication is specific to the characteristics of the brand. In the iPhone case, the specific virtues of iPhone would be the subject of communication. This phenomenon is typically presented in the business press to motivate managers to invest in customer satisfaction (Pruden and Vavra 2004; Reichheld 2006). Category-level communication is about the category as a whole and affects the adoption decision of the product category. In the iPhone example, such communication would be about the smart phone category. The research literature implies evidence of category-level effects generated by users of brands in the category. That is, consumers often use information on specific brands to generalize to new products in the category and make inferences from category-level information on specific brands in the category (e.g., Meyers-Levy and Sternthal 1993). The decision regarding the specific brand eventually purchased may depend on other factors, including brand equity, price, and availability. For electronic appliances, for example, interpersonal communications often affect the adoption at the category level, while the final decision is made later, based on issues such as price,

convenience, or brand equity of a specific brand (Gardyn 2003).

The distinction between category- and brand-level effects has been examined in the marketing literature on topics such as positioning strategies (Sujan and Bettman 1989), consumer choice (Nair, Dubé, and Chintagunta 2005), third-party recommendations (Shaffer and Zettelmeyer 2002), and advertising effects (Bass et al. 2005; Chakravarti and Janiszewski 2004). Yet a similar investigation has not been conducted on the different types of interpersonal communications and their respective effects on market dynamics. However, relevant behavioral research suggests that communications effects work at both the category and the brand levels and that the extent to which information on one brand affects consumer perception of other brands depends on factors such as the similarity between the brands and the nature of the decision-making process (Grewal, Cline, and Davies 2003).

The translation of brand- and category-level communications into within- and cross-brand influences can occur in multiple ways. Consider a user of Brand A who communicates with a prospective adopter about the product. Usually, positive brand-level communication leads to the purchase of the same brand. Brand-level communication can also lead to the eventual purchase of a competing brand (Brand B). This can happen in the case of category-level communications or, alternatively, with negative word of mouth. The latter case may be a less common case across categories because brand owners' positive word of mouth is more common than negative word of mouth (East, Hammond, and Wright 2007). Category-level communication influences the adoption decision of the category, which in turn translates into the purchase of either Brand A or Brand B. Thus, the decision to adopt Brand A can occur as a result of both category- and brand-level communications, and Brand A can gain users as a result of both its own users and the users of the competing brands.

The translation of category- and brand-level communications into cross- and within-brand influences is a promising area of research, most likely demanding individual-level data. This transformation depends on several factors, such as brand equity, price, or the extent of perceived similarity among brands. In some cases, decision making may be described by a two-stage process, in which the consumer first adopts the category and then decides on the brand. Here, a nested logit analysis may be necessary.

Modeling the Effect of Within- and Cross-Brand Communications on Growth

Consider a growing market for a new product, with multiple similar competing brands in the same category. We follow recent brand growth models (e.g., Krishnan, Bass, and Kumar 2000) and assume a common pool of potential adopters for the various brands. An alternative is to assume that each brand has its own unique market potential, such as in the pioneering work of Peterson and Mahajan (1978) and in some later works (Mahajan, Sharma, and Buzzell 1993; Shankar, Carpenter, and Krishnamurthi 1998). This

assumption may fit a case in which brands differ so widely that they focus on discrete consumer pools; yet it is less suited to the case of similar brands in the same category.

Although the new product growth modeling literature has focused mostly on the category level, marketing modelers increasingly use diffusion models to study the growth of competitive markets; thus, we use a diffusion framework and define the following variables and parameters:

$N_i(t)$ = number of adopters of brand i at time t ;

$N(t)$ = total number of adopters at time t —that is,
 $N(t) = \sum_i N_i(t)$;

m = common market potential;

p_i = parameter of external influence for brand i ;

q_i = within-brand influence on brand i ; and

q_{ij} = cross-brand influence of brand j on brand i .

The equations that govern the growth of brand i in a multibrand market are given by the following Bass-type equation set (for the two-player case, see Savin and Terwiesch 2005):

$$(1) \quad \frac{dN_i(t)}{dt} = \left[p_i + \frac{q_i N_i(t)}{m} + \sum_{j \neq i} \frac{q_{ij} N_j(t)}{m} \right] (m - N).$$

Adopters of brand i (N_i) spread brand-level communications by contacting and converting nonadopters ($m - N$) at a rate of q_i to adopt brand i . In addition, because of cross-brand influence, adopters of the competing brands j contact and convert nonadopters ($m - N$) to adopt brand i at a rate of q_{ij} . Thus, a potential adopter adopts brand i as a result of the combination of within-brand communications from the customers of brand i and cross-brand communications from the adopters of the competing brands j . Note that the cross-brand communications spread by the adopters of brand i are counted in the corresponding equations of the competing brands j , as are the brand-level communications spread by adopters of brands j . Note also that consistent with much of the diffusion literature, we do not explicitly model negative word of mouth if it exists but rather regard the overall resultant influence of each brand's customers (for modeling negative communications, see Goldenberg et al. 2007).

This equation generalizes other models that describe competitive growth. When $q_i = q_{ij}$ —that is, when within-brand influence is equal to cross-brand influence—the model is similar to that of Krishnan, Bass, and Kumar (2000); that of Kim, Bridges, and Srivastava (1999); the basic model of Givon, Mahajan, and Muller (1995); and one of the five models of Parker and Gatignon (1994). The underlying assumption is that there is no relevance to the brand ownership of the person who spreads the communications. However, if $q_{ij} = 0$, only within-brand influence is present, and the model is similar to that of Kalish, Mahajan, and Muller (1995); another model of Parker and Gatignon (1994); and that of Mahajan, Sharma, and Buzzell (1993). In most cases, however, both cross-brand and within-brand influences can be expected, and their respective magnitudes may not necessarily be equal. This approach was recently taken by Savin and Terwiesch (2005), who examined analytically optimal entry time in a duopoly market. Among their findings was that optimal entry time depends on the

ratio of cross-brand to within-brand influence. Note also that the interpretation of the growth parameters as communications parameters is well established in marketing.

Similar Brands, Different Entry Times

The model in Equation 1 can be used to explore various research questions, such as investment in marketing resources, the influence of brand characteristics on growth, and optimal entry times. One scenario of interest is the dynamics of a market with a first entrant and a follower. As we demonstrate shortly, this case, in addition to being common in many markets and industries, illustrates well the differential effects of cross- and within-brand influence on market growth. Competitive dynamics themselves may generate a perceptual difference in the two brands, either because of an actual difference or because of the entry time perceptual effects (Golder and Tellis 1993; Kerin, Varadarajan, and Peterson 1992). This will be captured in the difference in the diffusion parameters q_i and p_i for brand i in Equation 1. Because we want to isolate the effects of cross-brand and within-brand influence, respectively, and not deal with perceived differences that have been considered elsewhere, we focus on the case of two brands that are similar in both their product- and brand-related attributes; thus, we assume that $q_i = q_j = q$ and that $q_{ij} = q_{ji}$ and $p_i = p_j$.

Without loss of generality, we assume that firm i was first to market and that firm j joined at time t_0 , so that the initial conditions are $N_i(t_0) = N_0$, $N_j(t_0) = 0$. Under these conditions and because we know that the category-level solution is a Bass function, the model can be solved analytically to yield the following for $p_i = p_j$ (for the more general case where $p_i \neq p_j$, see Web Appendix A at <http://www.marketingpower.com/jmmay09>):

$$(2) \quad N_k(t) = (m/2) \frac{S - e^{-(P+Q)t}}{S + (Q/P)e^{-(P+Q)t}} + (-1)^{k+1} m \frac{(S+Q/P)^{\alpha-1} (S-1)/2}{[S + (Q/P)e^{-(P+Q)t}]^{\alpha}},$$

where k receives the value of 1 for the pioneer and 2 for the follower, $P = p_i + p_j$:

$$Q = q + q_{ij}; S = \frac{m + (Q/P)N_0}{m - N_0}; \alpha = \frac{q - q_{ij}}{q + q_{ij}}.$$

The first term of Equation 2 is the Bass function with nonzero initial condition. Parameter S represents the effect of the additional initial seed of adopters, which Muller, Peres, and Mahajan (2007) call the “seeding factor.” The second part of Equation 2 is added to the first entrant and is subtracted from the follower, representing the asymmetry in initial conditions. Summing up Equation 2 for both firms yields the Bass equation with nonzero initial conditions.

The Interaction-Based Advantage of the First Entrant

We now turn to examining the dynamics of the difference in number of users between the first entrant and the follower for similar brands. We define the gap between the firms as

the difference in the number of customers between the first entrant and the follower, or $N_i(t) - N_j(t)$. To understand how the gap changes with time, we take the derivative of the difference between the number of customers of the first entrant and that of the follower. From Equation 1, we obtain the following:

$$(3) \quad \frac{dN_i(t)}{dt} - \frac{dN_j(t)}{dt} = (q - q_{ij})[N_i(t) - N_j(t)][m - N(t)].$$

Note that Equation 2 implies that at any given point in time, $N_i(t) > N_j(t)$. Assume now that the intensity of within-brand influence is stronger than that of cross-brand influence ($q > q_{ij}$). Because all parts of the right-hand side of Equation 3 are positive, the derivative is positive, which means that the gap grows with time. Therefore, we can state the following:

P_1 : When within-brand communication is more intense than the cross-brand influence ($q > q_{ij}$), the gap between the first entrant and the follower grows over time.

As we discussed previously, because it is expected that in actual markets, and in the presence of positive communications, within-brand communication is more intense than that of cross-brand influence, we expect that the growing gap prevails in the case of similar brands. We label this phenomenon the “interaction-based advantage” of the first entrant. To understand the intuition behind the interaction-based advantage, we consider the point of competition entry. The first entrant has N_0 customers, acquired during its time as a monopoly, while the follower has zero customers at entry. This initial core group of the first entrant’s customers generates both within-brand communications, which favor the first entrant, and cross-brand communications, which assist the follower. Because the within-brand communications are stronger than the cross-brand communications, the first entrant, which initially has more customers, will acquire more new customers in subsequent periods, customers who, in turn, disseminate communications, which in turn reinforces the initial advantage. Thus, the initial bulk of N_0 customers forms an increasing return asset to the first entrant.

The Dual Pattern

To describe the full pattern of competitive growth under communications effects, we need to examine not only the dynamics of adoption over time but also the point of entry of the follower. Thus, we examine the initial rate of adoption for the follower and compare it with that of the first entrant. Formally, we compare the initial slope of each entrant’s growth curve. According to Equation 1, the initial slope of the first entrant at its time of entry ($t = 0$) is given by pm , while the initial slope of the late entrant at its time of entry ($t = t_0$) is given by $(p + q_{ij}N_0/m)(m - N_0)$, where N_0 is the number of the first entrant’s customers at the time of competition entry. A straightforward computation shows that if $p < q_{ij}(1 - N_0/m)$, the initial slope of the late entrant $N_j(t)$ will be steeper than that of the first entrant, $N_i(t)$.

It follows that the initial growth of the follower is faster than that of the first entrant, as long as two conditions are satisfied: First, the level of the external influence parameter

must be lower than that of cross-brand influence. Although empirical data on cross-brand communications are not available, our empirical analysis suggests that, on average, the level of cross-brand internal effect (q_{ij}) is stronger than that of the external influence for the follower (p_j). In a more general sense, diffusion internal influence parameters are considerably larger than external influence ones (Mahajan, Muller, and Wind 2000). Thus, this outcome can be expected.

The second condition is that the follower must enter the market early enough, in which case $(1 - N_0/m)$ is large enough. Note that N_0/m is the percentage of the long-term market potential captured by the pioneer when the follower enters. In the data we present next for the Western European cellular market, the average of N_0/m across 16 countries is estimated at 7%. Data from other studies also suggest that rarely did the pioneer capture a considerable portion of the market potential before the competition entered (Golder and Tellis 1993; Srinivasan, Lilien, and Rangaswamy 2004).

Thus, because of the expected size difference between external and internal influence parameters, the external influence parameter of the later entrant p_j may indeed be frequently lower than a multiplication of q_{ij} by a number not much lower than 1, and this will satisfy the condition for the shorter takeoff time of the follower.

P₂: If the cross-brand communication influence is stronger than the external influence and the follower enters the market early enough, its initial growth will be faster than that of the first entrant.

To understand the rationale behind this proposition, note that when the follower enters the market, two forces initially shape its growth compared with the first entrant. On the one hand, the follower can enjoy cross-brand influence from the first entrant, thus providing an advantage over the first entrant, which had no other brand from which to draw influence. On the other hand, the market potential is not as large as it was when the first entrant entered, thus diminishing the effect of both cross-brand and within-brand influences. So, if cross-brand influence is strong enough and entry is early enough, the initial adoption rate for the follower is higher.

From *P₁* and *P₂*, when the follower enters the market early enough, we can expect a pattern of initial high growth for the follower but a growing gap in favor of the first entrant, all else being equal. We label this pattern “the dual pattern.” Such a combination of opposing effects can be a source of misinterpretation for managers and industry analysts if the early rise of a second entrant is interpreted as an indication of future takeover of the market because it may only be part of a pattern that eventually leads to the first entrant getting stronger.

Will the Follower Become the Market Leader?

The interaction-based advantage we noted may be just one source of advantage or disadvantage of market players. There are many examples in which pioneers did not survive in the long run or at least lost their market leadership (Golder and Tellis 1993; Srinivasan, Lilien, and Rangaswamy 2004) and theoretical reasons to believe that later

entrants will sometimes have an advantage—for example, because their technology is perceived as superior (Bohlmann, Golder, and Mitra 2002). Our approach does not imply that later entrants cannot eventually become the market leader in terms of sales. In Equation 2 and the subsequent analysis, we focus on markets for similar brands so that we can highlight the within-brand and cross-brand communication effects separately from other effects. However, the basic model, as presented in Equation 1, allows the communication parameters p and q for each brand to differ, reflecting a possible difference among the brands. If the later product is perceived as superior, it can eventually become the market leader, consistent with the many examples of the eventual market leadership of a latecomer (Golder and Tellis 1993).

However, to become the market leader, or at least close the gap, a superior latecomer must overcome the interaction-based advantage that still exists as a result of the within-brand effect of the pioneer. How large should the perceived quality difference be for the follower to overcome the interaction-based advantage of the pioneer? Although this question cannot be answered analytically, we can simulate the growth process based on Equation 1 to find out the answer numerically (see Web Appendix B at <http://www.marketingpower.com/jmmay09>). With the average parameters obtained in our empirical analysis (we describe this subsequently), the growth parameters of the followers needed to be more than twice those of the pioneer for the follower to overcome the interaction-based advantage of the pioneer and catch up to it.¹ We summarize this finding in the following proposition:

P₃: The growth parameters of the follower (p and q) must be substantially larger than the corresponding growth parameters of the pioneer for the follower to overcome the interaction-based advantage of the pioneer and catch up to it.

The Western European Cellular Market

In this section, we empirically explore the dual pattern, aiming to examine the robustness of the stylized model predictions in an actual market setting in which brands are similar. This analysis comprises three stages: First, we explore the prevalence of the dual pattern in cellular markets in Western Europe. Second, we measure the magnitude of cross- and within-brand influences to determine how

¹We conducted a (Mathematica-based) extended simulation using a full factorial experiment on the model parameters. For each parameter combination, we measured the amount by which p and q of the follower should be multiplied to overtake the pioneer. The algorithm determined the minimum multiplier needed for the newcomer to overtake the pioneer at a given time point (heuristically set at 30). This is a conservative choice because if we wanted the follower to become the leader earlier, multipliers should have been higher. The result of these simulations is that the growth parameters of the follower needed to be more than 2.14 the size of the pioneer for the follower to overcome the interaction-based advantage of the pioneer and catch up to it (for details, see Web Appendix B at <http://www.marketingpower.com/jmmay09>).

they comply with the conditions stated in the formal analysis. Third, we test whether there is an empirical association between cross- and within-brand influences and the growth of the gap over time, and we test the validity of alternative explanations.

The Data

Obtaining detailed brand-level growth data for our case is not trivial. First, most empirical analysis of new product diffusion has been conducted at the category level, for which data are readily available. Second, data quality problems arise in the early growth of the product life cycle (Golder and Tellis 1993). For example, because we used survey data in retrospect, successful late entrants that were not actually the first entrants were considered pioneers, while failed pioneering efforts were not considered (Hauser, Tellis, and Griffin 2006). Finally, we investigated a market in which brands are similar to control for other factors that may create noise in the data.

We obtained a high-quality brand-level growth database for the European cellular service industry. Cellular markets are both relatively new and highly documented. Thus, they have been used for market growth analysis that focuses on topics such as the diffusion of successive generations of products (Danaher, Hardie, and Putsis 2001), optimal pricing (Danaher 2002), and multinational category-level diffusion (Dekimpe, Parker, and Sarvary 1998). Because of the attention this significant market has drawn from its birth, some private market research firms have collected data not only on growth but also on key performance indicators, such as churn, price, and quality.

Our study focuses on the Western European cellular service markets, which were the first to be launched commercially; thus, these markets provide adequate data for examining pre- and postcompetition growth. These markets were monitored from their initial stages, and data quality and richness are superior to those of most other industries. Unlike markets such as Japan or the United States, in which the cellular market is fragmented and composed of several service providers, in Western Europe, each of a small number of competitors enjoys full coverage in its respective country, making the competition structure straightforward.

Importantly, this industry has been regulated, leading to two favorable consequences for our purposes. First, the cellular industry began its growth in a monopoly market structure. Only at a later stage were one or more competitors allowed to enter the market. Thus, we can identify exactly when the first entrant began and when others joined. In addition, market entry of the follower can be treated as an exogenous factor, as in our model. In addition, because of regulation, many operational aspects of the firms were monitored and controlled to support long-term competition, among them some aspects of pricing, switching costs, availability of infrastructures, and other barriers to entry (European Commission Council 1999). For example, bundling the cellular service with a regular telephone line offered by a current market player was not allowed.

Thus, regulation considerably reduced the noise associated with the reaction of the first entrant to the entry of the

follower and created a situation of rather similar brands operating in the same market. In a sense, these cellular markets can be viewed as a large-scale, natural “market laboratory” that enables us to study the effect of within-brand and cross-brand communications on growth. The data set contains annual subscriber data for each provider in the 16 major competitive markets in Western Europe, from their launch until the end of 2005. Measurements are made on December 1 of each year. We excluded minor markets, such as Andorra, Monaco, Luxembourg, and Greece, where the competitive structure was breached early on as a result of mergers of operators. The data are provided by the World Cellular Information Service database, which is widely used in the cellular industry and contains subscriber data and some operational data. We also searched the relevant business press to track special events and regulatory actions.

All the markets in our data set began as monopolies, usually of state-owned telecommunication companies that had provided landline services. Most were opened to competition during the 1990s, with an average monopoly time of 7.8 years. The number of service providers ranged between two and five per country. On average, the first two entrants in the country occupy 78.7% of the market share. Thus, to be consistent with the focus of the model we presented and to keep the analysis simple, we focused on the first two entrants in each country.

One exception is the United Kingdom, where the third entrant (Orange) later became equivalent in size to the first two and even a market leader. Orange’s extraordinary brand-building efforts in England are well documented and, in a sense, may not be consistent with the “similar brand” approach of the basic model in Equation 2. To be consistent with the other countries, we still analyze the first two firms in the United Kingdom but note that this case may not fit our approach well. In three countries—Ireland, Sweden, and the United Kingdom—the original first entrants did not take off, mainly because of a lack of investments by the service provider (in the United Kingdom, for example, British Telecom was awarded the license, but it eventually decided not to invest resources in mobile telephony). Thus, for these countries, we viewed the first entrant as the first service provider that took off. Table 1 provides a list of the cases we used.

The Ubiquity of the Dual Pattern

We begin with a simple descriptive analysis of the dual pattern phenomenon. Figure 1 illustrates the number of subscribers over time for the 16 countries of the data set we analyzed. In 15 of the 16 countries, the first entrant remained the market leader.

Considering first the early growth of the later entrant (P_2), we compared the takeoff time of both the first entrant and the later entrant. To identify takeoff, we used Tellis, Stremersch, and Yin’s (2003) threshold approach. Table 1 presents the takeoff points for the firms in our data set, from which the following result could be ascertained:

Result 1: The takeoff time of the late entrant is significantly shorter than that of the first entrant. While average

TABLE 1
Cellular Service Providers and Their Takeoff Time

| Country | First Entrant | | | Second Entrant | | |
|----------------------|--------------------|---------------|----------------------|--------------------|---------------|----------------------|
| | Operator | Year of Entry | Takeoff Time (Years) | Operator | Year of Entry | Takeoff Time (Years) |
| Austria | Mobilkom | 1985 | 6 | T-Mobile | 1996 | 2 |
| Belgium | Belgacom | 1987 | 8 | Mobistar | 1996 | 2 |
| Denmark | TDC Mobile | 1982 | 12 | Sonofon | 1992 | 2 |
| Finland | TeliaSonera | 1982 | 7 | Elisa (Radiolinja) | 1992 | 3 |
| France | France Telecom | 1985 | 9 | SFR | 1989 | 7 |
| Germany | T-Mobile | 1985 | 7 | Vodafone D2 | 1992 | 5 |
| Iceland | Iceland Telecom | 1985 | 9 | OG Vodafone | 1998 | 2 |
| Ireland | Vodafone | 1993 | 3 | O2 | 1997 | 2 |
| Italy | TIM | 1985 | 6 | Vodafone Omnitel | 1995 | 2 |
| The Netherlands | KPN Mobile | 1985 | 10 | Vodafone | 1995 | 2 |
| Norway | Telenor | 1982 | 9 | Netcom | 1993 | 2 |
| Portugal | TMV | 1989 | 8 | Vodafone | 1992 | 4 |
| Spain | Telefonica Moviles | 1982 | 13 | Vodafone | 1995 | 2 |
| Sweden | TeliaSonera | 1982 | 7 | Tele2; Vodafone | 1992 | 2 |
| Switzerland | Swisscom | 1987 | 8 | TDC | 1998 | 2 |
| United Kingdom | Vodafone | 1985 | 8 | T-Mobile | 1993 | 6 |
| Average takeoff time | | | 8.1 | | | 2.9 |

takeoff time for the first entrants was 8.1 years, average takeoff time for the second entrants was only 2.9 years.

Other factors can also affect a second entrant's rapid takeoff, such as the overall tendency of takeoff to shorten over the years (Tellis, Stremersch, and Yin 2003). A way to still consider this phenomenon in the context of our model is to examine the existing penetration of the pioneering brand. Our formal analysis (see P_2) shows that if market penetration at the time of the follower's entry is not too high, the model predicts that the more customers the first entrant has, the easier it is for the follower to take off using cross-brand communications. Thus, we can expect that the earlier takeoff of the follower is associated with higher market penetration of the first entrant at the point of follower entry. In our data set, the average penetration rate of the first entrant at the time of competition entry is 7%; thus, we expect the correlation to hold. Indeed, the Pearson correlation between takeoff time and the first entrant's penetration rate at competition entry is $r = -.46$ ($p = .07$).

Result 2: A higher market penetration of the first entrant at the point of entry of the follower is associated with an earlier takeoff of the follower.

Another aspect of the dual pattern is the growing gap in the number of users. Recall that according to the model, if the within-brand influence is stronger than the cross-brand influence, the gap is expected to increase over time; however, if both communication types are equal, their curves are parallel. A decrease in the gap is expected in rarer cases of negative within-brand information. We expect that in most cases, the gap will increase or at least remain constant over time. The gap-widening rate reflects the change in the difference in the number of subscribers between the first and the second entrant for each period t since the competi-

tive entry. To enable comparison between countries, this difference is normalized by the market potential; that is, for a country y , the gap at time t is defined as $gap_{yt} = [N_{iy}(t) - N_{jy}(t)]/m_j$. Then, for each country y , we performed a regression of this difference over time: $gap_{yt} = \alpha_{0y} + \alpha_{1y}t + \epsilon_y$. The slope α_{1y} of the change can serve as an indicator of the widening of the gap and thus is our measure for the gap-widening rate. Table 2 presents the results of this measurement for all the countries in our data set. In 12 of the 16 countries, the slope is positive; that is, the gap increases over time. In four countries, it is not significantly different from zero ($p > .05$). In none of the countries does the gap decrease significantly over time. These results comply with the data in Figure 1 for all the countries except Germany.²

Result 3: The gap in the number of subscribers between the first entrant and the follower either increases on average over time (12 of 16 countries) or remains constant on average (4 of 16 countries). We did not observe an average decrease of the gap in any of the countries.

The Magnitude of Within- and Cross-Brand Effects

Our next step is to obtain measurements of the within- and cross-brand influences. We used Equation 1 for the first and second entrant in each country, and as in the formal analysis, we assumed that $q_i = q_j = q$ and that $q_{ij} = q_{ji}$. One change we made from the formal model in the previous section was to allow a difference in the values of external influence parameter p , thus reflecting the capacity of brands to

²In Germany, Vodafone was closing the gap to the first entrant (T-Mobile), and the gap was opened only in 2000; therefore, there is a period of a decreased gap and a period of an increased gap that our single linear measure cannot capture.

FIGURE 1
The Dual Pattern of Follower's Initial Fast Growth and First Entrant's Increasing Later Gap

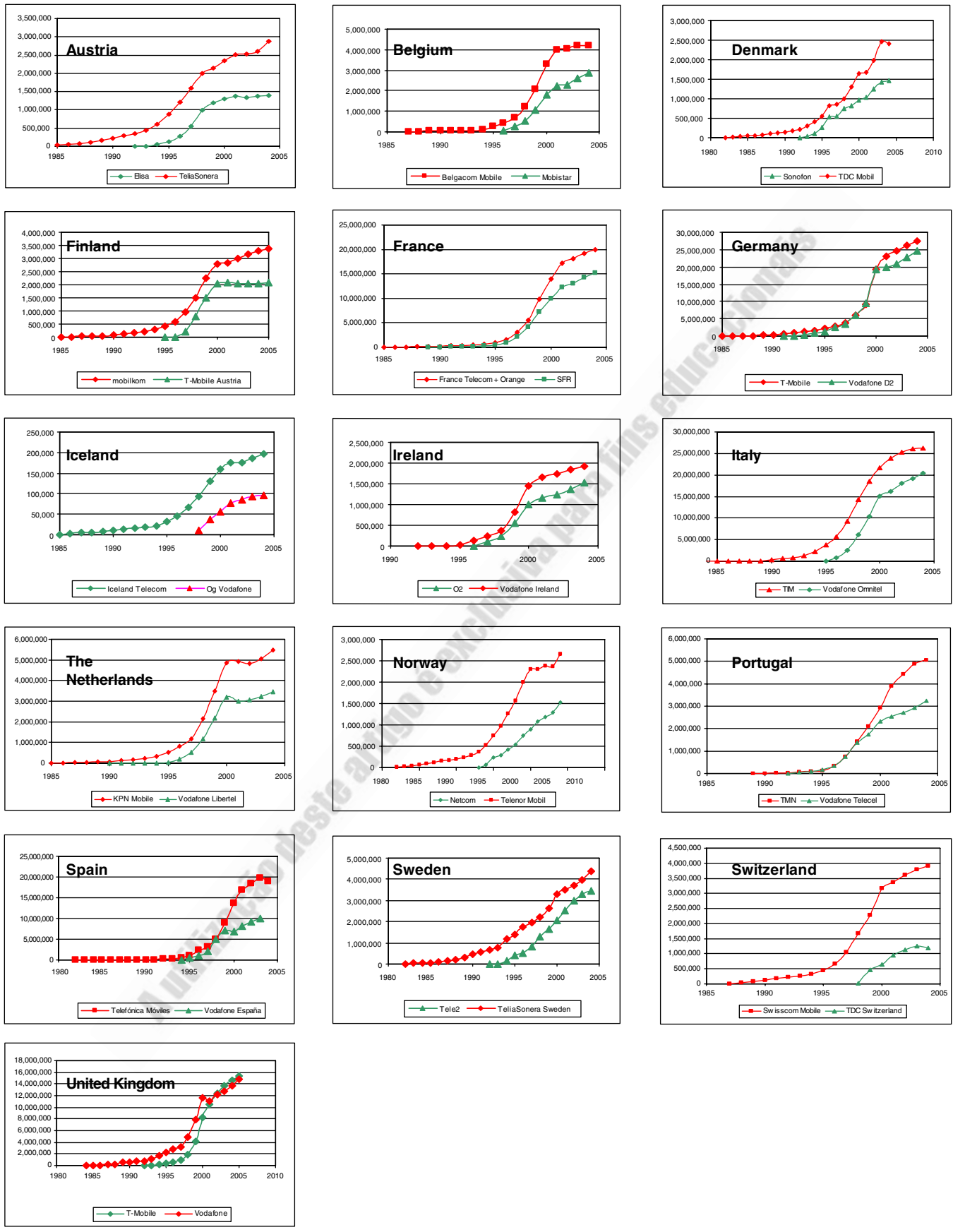


TABLE 2
The Gap-Widening Rate Estimation (Average Change Rate of Gap in Number of Subscribers over Time)

| Country | Slope (Widening Rate) | p-Value | Trend |
|-----------------|-----------------------|---------|----------|
| Austria | .0140 | .0005 | Increase |
| Belgium | .0197 | .0082 | Increase |
| Denmark | .0157 | .0000 | Increase |
| Finland | .0133 | .0043 | Increase |
| France | .0104 | .0000 | Increase |
| Germany | .0050 | .0055 | Increase |
| Iceland | .0074 | .0758 | Constant |
| Ireland | .0114 | .0219 | Increase |
| Italy | .0032 | .2450 | Constant |
| The Netherlands | .0282 | .0001 | Increase |
| Norway | .0196 | .0001 | Increase |
| Portugal | .0212 | .0000 | Increase |
| Spain | .0344 | .0003 | Increase |
| Sweden | -.0001 | .9469 | Constant |
| Switzerland | .0322 | .0014 | Increase |
| United Kingdom | -.0081 | .0430 | Constant |

affect consumers through their promotional activities. For each country, we estimated the penetration curves simultaneously, using seemingly unrelated regression (PROC MODEL in SAS). Table 3 presents the parameter values.

Table 3 shows that for all the countries except Germany, cross-brand influence is weaker than within-brand influence ($q_{ij} < q$). The average ratio of q_{ij} to q is .55; that is, it could logically be expected that there is significance to the brand ownership of the adopter who is engaged in the communication (i.e., a communication with an adopter of a brand leads to greater chances of the consumer acquiring that brand). This result illustrates the importance of explicit representation of within-brand and cross-brand influences: Considering the two influences equal leads to overestima-

tion of the cross-brand influence and underestimation of the within-brand influence, a bias that might harm the fit and forecasting.

Other Forces at Play

Our basic analysis of the dual pattern assumed similar brands, but in real life, multiple factors can challenge this assumption, affect first entrants' advantage, and possibly provide alternative explanations to the dual pattern we witnessed. Thus, we consider some of the major alternative factors that might serve as explanations for the dual pattern in the markets we analyzed, and we compare them with the communications explanation.

Price difference (PriceDiff). Prices can have significant influence on market evolution. A first entrant's ability to reduce its prices sharply enables it to draw more customers and open up a gap. Our data set contains quarterly price data (for most quarters) for a minute of peak airtime, in U.S. dollar nominal values, since 1993 (no price data are available for most of the current decade, in which the database managers stopped assessing average price because of the growing complexity of the plans). In cases in which competition entered after 1993, we used data from the competition's entry date. The price measure we have is the average price for all programs, including roaming charges to other networks. We operationalized this variable for price differences as the average of the difference in price per minute between the first and the second entrants.

Although we use the value of PriceDiff in a multivariate analysis, even an initial analysis of the data indicates that price may not be a good explanation for the gap. Of the 16 countries whose data we studied, the average price of the first entrant was lower than the average price of the follower in only 2 countries. If anything, PriceDiff should have helped close the gap, not open it. To examine this point further, we used the generalized Bass model (Bass, Krishnan, and Jain 1994). Thus, Equation 4 is a generalized Bass

TABLE 3
Parameter Estimation for the Western Europe Cellular Market

| Country | p_i : First Entrant | p_j : Follower | q : Within-Brand | q_{ij} : Cross-Brand | q_{ij}/q | m | R^2 : First Entrant | R^2 : Follower |
|-----------------|-----------------------|------------------|--------------------|------------------------|------------|-------------|-----------------------|------------------|
| Austria | 0 | 0 | .5924* | .4423* | .747 | 5,257,091* | .922 | .867 |
| Belgium | 0 | .0083 | .824* | .1372 | .167 | 6,859,488* | .924 | .832 |
| Denmark | .0023 | .0112* | .3157* | 0 | .000 | 4,429,937* | .437 | .502 |
| Finland | 0 | 0 | .4234* | .1667* | .394 | 4,174,702* | .709 | .193 |
| France | .0013 | .0031 | .7051* | .0174 | .025 | 36,563,972* | .797 | .777 |
| Germany | .0024 | 0 | .1969 | .7183* | 3.648 | 52,182,828* | .69 | .498 |
| Iceland | 0 | .0027 | .4562* | .2584* | .566 | 293,597* | .777 | .917 |
| Ireland | .0114 | .0316* | .7163* | 0 | .000 | 3,546,547* | .557 | .765 |
| Italy | .0057 | 0 | .4086* | .2899* | .709 | 47,632,623* | .751 | .844 |
| The Netherlands | 0 | 0 | .6563* | .3174* | .484 | 8,527,233* | .203 | .757 |
| Norway | .0028 | .0089 | .2949* | .0496 | .168 | 4,906,969* | .257 | .699 |
| Portugal | .0079 | .0026 | .6405* | 0 | .000 | 8,567,577* | .876 | .41 |
| Spain | .0006 | .0097 | .8392* | 0 | .000 | 28,867,446* | .871 | .306 |
| Sweden | .0015 | 0 | .2262* | .1764* | .780 | 8,417,699* | .586 | .853 |
| Switzerland | .0003 | .0045 | .5457* | .1775* | .325 | 5,239,988* | .713 | .659 |
| United Kingdom | 0 | 0 | .4078* | .3472* | .851 | 29,164,818* | .31 | .82 |

* $p < .05$.

model extension of Equation 1, where f is some decreasing function of price:

$$(4) \quad \frac{dN_i(t)}{dt} = \left[p_i + \frac{q_i N_i(t)}{m} + \sum_{j \neq i} \frac{q_{ij} N_j(t)}{m} \right] \left[m - \sum_i N_i(t) \right] f(\text{price}).$$

To apply the new model to the data, using exponential function, we extrapolated the years during which no price data were available, and we applied a linear effectiveness function f in Equation 4. Of the 12 countries in which the model converged, the price coefficient was not significant in 7 of them, but the coefficient had the right (negative) sign in the 5 significant ones. To test whether the remainder of the parameters changed in these countries after introducing the price data, we tested the new parameters against that obtained with Equation 1. The 5 countries in which price was significant have five parameters each (two each for p and q and one for the market potential). Of these 25 parameters, 24 have not changed (at the 5% significance level).

Network effects. Network effects can considerably influence the growth of markets for new products (Stremersch et al. 2007). A key rationale as to why network effects may affect customer choice in cellular markets is the widespread pricing schemes that offer lower rates for talking within the network (Birke and Swann 2006). Network effects are of special interest in our case because they create an increasing return mechanism based on the number of customers, which may be difficult to distinguish empirically from the communications effects on which we focus.

Although distinguishing between the two is indeed nontrivial, a few issues should be taken into account: First, network effects should indeed help bolster the market leader. Thus, in a network effects–dominated scenario, the follower would have a difficult time initially taking off. However, this is not consistent with the fast follower takeoff that we actually observe. In contrast, within- and cross-communications processes explain both the early rise of the follower and the long-term disadvantage of the first entrant that we empirically observe. Second, the extent to which the number of subscribers captures network effect in our case is questionable. For example, Birke and Swann (2006) study the cellular market in the United Kingdom and conclude that though there may be some network effect that stems from the number of subscribers, the more dominant network effect stems from the choices of other members of the family (which is less relevant to us).

A support to that effect in the European market comes from the work of Turnbull, Leek, and Ying (2000), who conducted an in-depth study of consumer decision making in the U.K. cellular market. They find that though consumers were aware of market competitors in general, they were confused about not only the difference between them but also competitors' exact roles or positions within the structure of the industry. Turnbull, Leek, and Ying also find that among possible information sources, word of mouth

played the most important role in cellular choice. Finally, the finding that across our database average price was mostly lower for the followers' customers is important because it takes into account actual minutes talked both within and outside the network. Possibly, the follower cellular operators internalized their disadvantage due to the smaller network and lowered their prices accordingly. Consequently, price-related network effects may not have played a dominant role in the growth of these markets.

Churn difference (ChurnDiff). Churn, or customer defection, has historically had a considerable effect on competitive position in cellular markets. Churn rates are affected by customer satisfaction, switching costs, and the brand equity of the competitors. Theoretically, if the churn rates for the first entrant are much lower than that of the competitor, this may explain the gap. However, note that because the follower has considerably fewer customers after entry, the difference between the churn rates of the two must be large to explain a large gap in customers. Our data set contains quarterly data of monthly churn for most quarters since 1997 for all the countries studied except Belgium, Iceland, and Ireland. We operationalize this variable for churn differences as follows: For each country, the average churn level of each competitor is computed, and then the averages of the first and second entrant are subtracted. We use a single measure because the data are not complete and do not enable a quarter-by-quarter pair comparison.

In general, we found that the differences in churn rates were not large; indeed, they were surprisingly small (on average, across all countries, average monthly churn rate was 2.272% for the follower versus 2.261% for the first entrant). Yet, on average, in most countries, churn rates tended to be lower for the first entrants. In addition, we noticed that churn rates did not change much over the years. Exceptional cases are those in which number portability was introduced (as in Finland), which can cause a sudden increase in churn.

To examine the effect of churn further, we corrected the number of new customers in each period, taking into account churn, in line with Gupta, Lehmann, and Stuart's (2004) approach. We assume that at time t , the observed net differences in the number of customers of the pioneer (i) and the follower (j) are dN_i^{ob}/dt and dN_j^{ob}/dt , respectively. We denote with dN_i^m/dt and dN_j^m/dt the number of customers who joined from the market potential (i.e., the number of adopters). The churn rates are a_i and a_j . Thus:

$$(5a) \quad dN_i^{ob}/dt = dN_i^m/dt - a_i N_i + a_j N_j, \text{ and}$$

$$(5b) \quad dN_j^{ob}/dt = dN_j^m/dt - a_j N_j + a_i N_i.$$

Because we observed the number of adopters and know the churn rate, we can retrieve the actual number of adopters. To apply the new model to the data, we extrapolated for the years in which no churn data were available. Note that given the rather similar churn rates in our data, because the pioneer had more customers initially, its loss from churn was greater than that of the follower. Thus, following the approach we present here, to obtain the observed widening gap, the interaction-based advantage should by

TABLE 4
The Gap-Widening Rate Estimation for Observed and Churn-Compensated Data

| Country | Gap-Widening Rate on Observed Data | Gap-Widening Rate on Compensated Data |
|-----------------|------------------------------------|---------------------------------------|
| Austria | .0140 | .0533 |
| Belgium | .0197 | .0927 |
| Denmark | .0157 | .0644 |
| Finland | .0133 | .2151 |
| France | .0104 | .0251 |
| Germany | .0050 | .0122 |
| Iceland | .0074 | .1576 |
| Ireland | .0114 | .0609 |
| Italy | .0032 | .0223 |
| The Netherlands | .0282 | .0518 |
| Norway | .0196 | .0324 |
| Portugal | .0212 | .0460 |
| Spain | .0344 | .0802 |
| Sweden | -.0001 | .1334 |
| Switzerland | .0322 | .0972 |
| United Kingdom | -.0081 | .0296 |

even greater because the pioneer must overcome the churn. This is indeed what we find from an empirical analysis, compensating for churn (see Table 4).

Technology (%GSM). Pioneering advantage or disadvantage can be a function of the technologies the various market players use. In our case, however, the advantage is with the follower. The “technology vintage effect” indicates pioneering disadvantage in which the later entrant uses improved technology that enables higher quality and lower costs (Bohlmann, Golder, and Mitra 2002). Indeed, in the countries we analyzed, the first entrant entered with analog technologies and only later moved gradually over to digital technologies. Conversely, the second entrants entered offering all digital technology (GSM), which was considered superior, and the entire European market eventually moved over to this.

To quantify and observe possible technological differences among the competitors, we used a measure (%GSM) for the technological differences: the percentage of first entrant GSM users at competition entry. The assumption is that the higher this percentage, the smaller is the difference among the competitors.

Control of infrastructures (Penetration). Another source of pioneering advantage may be the control of resources the first entrant gains during its time as a monopoly. In the cellular industry, such resources can be locations of transmission antennas, established relationships with suppliers, and employees. We argued previously that the penetration level of the first entrant at the follower’s entry helps the follower initially reach takeoff. However, this penetration level can also serve as a proxy to the control of infrastructures and, thus, as an aid to first entrant advantage. Thus, the Penetration variable to be used is the penetration level (relative to the market potential) of the first entrant at competition entry. We note that despite the long time until the market became open to competition (7.8 years on average), the first

entrants did not manage to capture a large portion of the market: The average penetration rate at competition entry is estimated to have been just 7%.

Number portability (N-portability). A barrier of switching between providers of mobile services is the inability of consumers to continue the service with their current phone number. The 2002 Universal Service Directive of the European Union required mobile operators to implement number portability, thus reducing the switching costs to consumers. Some European countries implemented this change before the 2002 directive, and others did so much later. Thus, the earliest country in our list to implement number portability is England in January 1999, and the most recent is Austria in October 2004 (Electronic Communications Committee 2003; Smura 2004). We operationalize this variable by measuring the time each country took (in months) from the introduction of cellular service to the implementation of number portability.

Next, we examine the extent to which a communications pattern helps explain the gap in customers, compared with other factors we could quantify. The dependent variable is the gap between the first entrant and the follower, for which we use the gap-widening rate calculated in Table 2. For the independent communications parameter, we used the ratio of q_{ij} to q , or the ratio between the cross-brand and the within-brand influences. As Result 2 indicates, the stronger the within-brand effect than the cross-brand effect, the more the widening gap favors the first entrant. Thus, we expect that this variable’s coefficients will be negative; that is, the weaker the cross-brand influence than the within-brand influence, the higher is the widening rate of the gap. Additional independent variables are price difference, churn difference, penetration level of the first entrant at the follower’s entry, the percentage of GSM users by the first entrant at that time, and number portability. The regression used data from 12 countries, excluding the countries for which we did not have churn data, and Germany. The results appear in Table 5.

TABLE 5
Other Influences on the Widening Gap: A Two-Stage Process

| Parameter | Estimate | p-Value |
|---------------|----------|---------|
| Intercept | .02226* | .0297 |
| q_{ij}/q | -.02993* | .0620 |
| ChurnDiff | .07593 | .7572 |
| PriceDiff | .01060 | .8601 |
| Penetration | -.01134 | .8687 |
| %GSM | .02708 | .1161 |
| N-portability | -.00003 | .8421 |

* $p < .1$, $R^2 = 79\%$.

Notes: The variable q_{ij}/q represents the ratio of cross-brand to within-brand influences, and ChurnDiff and PriceDiff are the average difference in churn and price between the pioneer and the follower. Penetration and %GSM are the percent penetration and percent digital (GSM) of the pioneer at entry time of follower, and N-portability measures the time at which consumers could change providers while keeping their own mobile phone number.

Table 5 shows that the only significant variable is q_{ij}/q . As we expected, the coefficient is negative; that is, the weaker the cross-brand effect than the within-brand effect, the less the late entrant benefits from cross-brand influence, and therefore the advantage of the first entrant over time increases at a higher rate. To validate this result further, we conducted an additional test. In the preceding analyses, we used as a dependent variable the measurements of the gap-widening rate presented in Table 2. Thus, we performed a two-stage process: (1) We computed the gap-widening rate, and (2) we tested its dependence on the variables. These two steps can be unified into a single regression that simultaneously measures the gap-widening rate and explains the widening. If the d_y are dummy variables for the country and x_k is the k th explanatory variable (q_{ij}/q , ChurnDiff, PriceDiff, Penetration, %GSM, and N-portability), the combined model is as follows:

$$(6) \quad \text{gap}_t = \alpha_{01}d_1 + \alpha_{02}d_2 + \dots + \alpha_{0Y}d_Y + (\beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_kx_k) t + \epsilon.$$

Excluding again the outlier of Germany, the regression results imply that, as in the previous analysis, the ratio of q_{ij} to q is significant. An additional source of influence that was significant in this analysis is the %GSM—that is, the percentage of GSM users of the first entrant at the time of competition entry. The variable %GSM is an indication of technological difference, or the level of technological substitution: Its sign is positive; that is, the higher the number of first entrant subscribers who already switched to GSM at competition entry, the lower is the technological advantage of the follower, a situation that favors the first entrant.

Other Models at Play

The Western European data enable us to compare the approach presented here with previously available models of brand growth. We compare three models, which represent three approaches to brand-level diffusion and the communication effect. The first is the model by Krishnan, Bass, and Kumar (2000) (KBK), in which cross-brand and within-brand influences are equal. That is, the information is only at the category level, and there is no importance to the brand ownership of the adopter who is the source of the communication. The second model is by Kalish, Mahajan, and Muller (1995) (KMM), in which the communications influence is only within brand. The third model is the one we present here, which allows for both within-brand and cross-brand influence:

$$(7) \quad \text{KBK: } \frac{dN_i}{dt} = \left[p_i + \frac{q_i(N_i + N_j)}{m} \right] \times (m - N_i - N_j),$$

$$(8) \quad \text{KMM: } \frac{dN_i}{dt} = \left(p_i + \frac{q_i N_i}{m} \right) \times (m - N_i - N_j), \text{ and}$$

$$(9) \quad \text{Current model (CM): } \frac{dN_i}{dt} = \left(p_i + \frac{q_i N_i}{m} + \frac{q_{ij} N_j}{m} \right) \times (m - N_i - N_j).$$

We first conducted a straightforward fit comparison of the three models. To compare the models meaningfully, we set the same number of parameters in each model by assuming in the CM that $q_i = q_j$ and $q_{ij} = q_{ji}$. We found that the fits are rather similar: The average R-squares for KBK, KMM, and CM were 64.6%, 63.4%, and 64.0%, respectively. Furthermore, the three models did not differ in their forecasting abilities using two-step-ahead predictions.

The advantage of the CM is captured in the less restricted description of the mechanism that drives brand-level growth. Specifically, to fit as well, the other two models must make assumptions that may not be robust and are unnecessary under our more general approach. Note that in its full version, the CM is a generalization of KMM and KBK; that is, KMM is the special case in which $q_{ij} = 0$, and KBK is the case in which $q_i = q_j$. The CM provides the required flexibility for describing both within-brand and cross-brand influences and, thus, the dual pattern. For example, consider the growth curves in the case of identical brands ($q_i = q_j$, $q_{ij} = q_{ji}$, and $p_i = p_j$): The KBK model generates parallel curves, with a sustainable advantage to the first entrant and a shorter takeoff for the follower. The KMM generates an increasing pioneering gap, with a long takeoff time for the follower. The dual pattern observed in our data of both short takeoff and an increasing gap is unique to the CM. The other models must assume difference in the diffusion parameters to obtain this pattern.

When the brands are not identical, any growth pattern can be generated; specifically, both KMM and KBK can generate the dual pattern. However, to achieve a dual pattern, specific combinations of p and q are required. Simulations that we conducted indicate that in KBK, q of the follower must be lower than q of the pioneer to generate the dual pattern. This is because the follower enjoys full cross-brand influence, and thus lower within-brand word of mouth suffices for its growth. For KMM, because the follower does not receive any cross-brand word of mouth, its growth is slow; thus, the follower needs to have higher q and p to reach typical growth patterns. There is no apparent theoretical or market-related reason to assume that q of the follower must be lower (or higher) than q of the pioneer; thus, it might be suspected that these values result from the constraints of full (KBK) or zero (KMM) cross-brand influence constraints, which are relaxed by the more general CM.

The Case of Multiple Players

Although the model presented in Equation 1 is suitable for multiple players, the empirical analysis focused on the case of two brands: a pioneer and a follower. To what extent would additional entrants change the dynamics presented here? Intuitively, the dual pattern dynamics should apply to more players as well. Later players enjoy the larger number of previous customers for a cross-brand effect that will drive takeoff. However, the interaction-based advantage of the previous players will make growth difficult, unless the third entrant is dissimilar, introducing a superior product that will draw adopters to it. Although obtaining a closed-form analytical solution for the case of more than two play-

ers has proved to be nontrivial, simulations we conducted for the case of similar brands indicate that this is indeed the case. In general, our data are also consistent with a disadvantage for further entrants. In the cellular markets we analyzed, the first two entrants captured approximately 80% of the market, and in only 1 of the 16 cases did the third entrant overtake one of the first two. These cases support the dynamics we expected for multiple players with similar brands. We also ran the empirical analysis with three players, and the resultant regression yielded similar results to the two-player case in terms of both their R-squares and their implications. In all the cases, except for that of the United Kingdom, there is a clear advantage of the first generation over the subsequent generations, and in all the cases, the takeoff of the third entrant is sharper than that of the second (this empirical analysis is available on request).

Discussion

We can summarize the results of this study as follows:

- The growth of a competitive new brand is influenced by the combination of effects from the brand's own customers (within-brand) and the competitor's customers (cross-brand).
- Because of the cross-brand effect, in a market that exhibits differential entry by similar brands, the follower often enjoys a shorter takeoff time than the pioneer.
- However, the pioneer may enjoy an interaction-based advantage due to a within-brands effect (i.e., an increasing return mechanism by which it can acquire more new customers as a result of the larger number of initial customers). In contrast to previously identified sources of pioneering advantage, this does not demand a differing perception among brands.
- The interaction-based advantage is just one factor that will eventually create the differential sales pattern. However, to overcome the interaction-based advantage, consumer perception of the follower must be considerably better than that of the pioneer.
- We label the combination of a fast takeoff for the follower and an overall growing gap in favor of the pioneer as the dual pattern. In the Western European cellular market, the dual pattern prevails in 14 of the 16 countries. The communication approach provided a better explanation than other straightforward alternative explanations.

Our approach follows the increasing interest of academic marketing researchers in brand-level diffusion (Krishnan, Bass, and Kumar 2000; Parker and Gatignon 1994; Peterson and Mahajan 1978; Shankar, Carpenter, and Krishnamurthi 1998), but it differentiates between the various types of customer communication. Our results indicate that the distinction between the types of communication is important, and they encourage future modelers of the brand level to study the consequences of this distinction further.

Interaction-Based Advantage and Pioneering Advantage

A rich literature in marketing and related fields examines sources of pioneering advantage and disadvantage and their consequences (e.g., Golder and Tellis 1993; Kalyanaram, Robinson, and Urban 1995; Srinivasan, Lilien, and Rangaswamy 2004). These sources include supply-side, or producer-based, sources and demand-side, or customer-

based, sources (Golder and Tellis 1993). Highlighting interaction-based advantage complements previous findings in this regard. This source is fundamentally different from other consumer-based sources because it exists with no perceived difference between the brands, while basically all identified consumer-based sources stem from a differing perception of the brand between earlier and later entrants. We also show how pioneering advantage can depend on the intensity of the consumers' communications behavior; that is, the more intense the brand-level communications, the greater is the advantage, though the advantage declines with increasing category-level (and, thus, cross-brand) communications.

Finally, interaction-based advantage is an increasing return phenomenon, in contrast to most perception-based advantages, which may fade as the later entrant becomes established in the market. This complements previous research on increasing returns in the product growth process that has often focused on markets with specific phenomena, such as network effects or declining costs (Eisenmann 2006). The interaction-based advantage may be more widely spread because it is not restricted to specific product markets. It is also consistent with the work of Arthur (1994), who notes that increasing return processes may dominate much of the economy and can be a by-product of human interactions in general.

Brand-Level Takeoff

As P_2 suggests, in many cases of similar brands, the takeoff of the follower is faster than that of the earlier entrants. This insight provides a contribution to the growing literature on new product takeoff. Until now, takeoff patterns have concentrated on the category level and have been explained by a host of factors, including price decline, social system, and culture characteristics; product category-specific factors; country-specific economic factors; and the intercountry effect (Golder and Tellis 1997, 2004; Stremersch and Tellis 2004; Tellis, Stremersch, and Yin 2003). However, managers are probably also interested in the brand level, not just the category level.

If we examine the brand level, it is reasonable to believe that the takeoff of the pioneer will be affected by the same factors that affect the category at large and have been identified in previous research. Indeed, if the first entrant is a monopoly for long enough, its takeoff will be the category takeoff. For the later entrants, this takeoff should be a function not only of the category-level factors (and for nonsimilar brands, differential perception) but also of the pattern of communication with the consumers of the existing brands. In what may seem counterintuitive to some managers, a larger number of pioneers' customers in a market may help the new entrant's takeoff, not the opposite.

The cross-brand effect has an additional implication. Recent research has called for customer profitability research to account for the value of the internal dynamics among customers (Gupta et al. 2006). Through a cross-brand effect, competitors' customers can have a considerable influence on the brand. This effect can be negative, as in the case of brand crisis (Dahlen and Lange 2006), or

positive, as in the case of new category growth. Thus, competitors' customers should have positive lifetime values, even if they do not buy from the firm, and their disadoption can harm the opposing brand (Hogan, Lemon, and Libai 2003).

The Ubiquity of the Dual Pattern

Although dual pattern should be more easily recognized in markets for similar brands, the forces we identify should be at work regardless of brand similarity. To what extent should a dual pattern in competitive growth markets be expected? This question is especially relevant because both empirical and conceptual work point to the possible advantage and eventual success of late entrants to markets (Hauser, Tellis, and Griffin 2006). There are two issues that determine the relevancy of the dual pattern across markets: (1) the power of brand-level communication and (2) the extent of brand dissimilarity.

The power of brand-level communication. In some markets, brand-level communication may not be a strong force that drives adoption. Consider the following examples:

- *Fast-moving consumer goods.* Diffusion theory is less relevant to the growth of fast-moving consumer goods, which are typically not as new or as risky as technological products. Empirical findings suggest that fast-moving consumer goods markets may indeed differ in terms of pioneering advantage from durable and industrial goods (Kalyanaram, Robinson, and Urban 1995).
- *Early stages of highly innovative markets.* We may not expect the interaction-based advantage in the early stages of markets for really new products. If the market is novel enough, the brand may not be the focus of communication so much as the product category. Thus, cross-brand communications, followed by brand-level marketing mix, will dominate.

The extent of brand dissimilarity. If the perceived difference among the brands is large enough, it will dominate the brand-level communication patterns we discussed here. In some cases, it will supply an additional advantage for the pioneer (though not necessarily an increasing returns one). Alternatively, it will help the later entrant. Although we have shown that a sizable difference between the brands is needed to overcome the interaction-based advantage, this can happen, especially in markets in which technological change is rapid, making it possible for later entrants to enjoy quality and innovation that first entrants did not (Bohlmann, Golder, and Mitra 2002; Shankar, Carpenter, and Krishnamurthi 1999).

We stress that even when brands are somehow dissimilar, cross-brand and within-brand integration continues to affect the market. The question is still which effects are stronger. Thus, the degree to which the dual pattern may affect markets should be examined per case and per product type. Consider the case of pharmaceuticals. Two similar drugs in the same category might be affected by within- and cross-brand influences, especially because social contagion affects physician decision making considerably (Bhatia, Manchanda, and Nair 2006). However, in some drug markets, later drug entrants may be more innovative (Shankar, Carpenter, and Krishnamurthi 1998), which should reduce the interaction-based advantage. The entry of generics

might be considered a good example for our case because the new brand is similar in terms of ingredients. Yet decisions on adoption of a generic drug may be made less by physicians and more by health maintenance organizations, which often try to push the lower-cost, generic drug to physicians. In this case, brand-level communication by physicians may not be the driver of growth.

Markets for Competing Standards

Markets in which brands compete for a standard provide variation on the framework we presented because competing brands may often be similar in most attributes, with differences stemming from network externalities, which are a social mechanism as well. The literature has argued that competing standards may slow the growth rate at the category level (Van den Bulte and Stremersch 2004), and the issue is the nature of this effect at the brand level. Although our model would not capture the phenomenon of potential adopters who wait to adopt until they can determine "who the winner is," when they adopt, we expect network externalities to complement the within-brand effect and amplify the increasing return phenomenon. Conversely, they will work against the takeoff of the follower. There is no "cross-brand" equivalent in the case of network effects, and the lower utility due to fewer users of the standard will likely affect the follower's adoption parameters, and thus we may not observe a dual pattern.

Managerial Implications

The distinction between within-brand and cross-brand effects on growth has significant managerial implications. It is necessary to draw the distinction between the two when conducting market research. Recently, managers have become increasingly aware of the need to research and even to affect interpersonal communications, such as word of mouth, as well as the notion that new tools to identify and build on these social affects are increasingly introduced (WOMMA 2006). Yet the distinction between the two types of interpersonal effects is rarely made, and conventional wisdom focuses only on within-brand influence. To realize fully the difference between the two types and to use this knowledge for prediction and planning, firms must explicitly try to differentiate between the two by better understanding the various sources of interpersonal communications.

The dual pattern we found presents additional challenges to managers who observe their own brand and that of the competition and to other stakeholders, such as market analysts. If other factors are controlled for, the shorter takeoff time of a second entrant should not be surprising. Because takeoff is used by managers as an important sign of the brand's health (Golder and Tellis 1997), the shorter takeoff time of the follower may mislead; it does not necessarily point to better acceptance of the market for a "better" product but rather possibly hitches a ride on the cross-brand effect. Thus, other perception-based measures are probably needed to indicate whether a second brand's shorter takeoff time is indeed an indicator of future success.

To realize the possible managerial biases generated by the dual pattern, consider the case of the cellular market in Sweden in the early 1990s. For ten years, beginning in

1982, the Swedish cellular market operated as a monopoly, with a single operator: TeliaSonera. In 1992, the market was opened up to competition, and a new service provider, Tele2, entered the market. TeliaSonera was a traditional, state-owned company, a monopoly of many years. Conversely, Tele2 was a new firm specifically designed to compete in the cellular market. Tele2 also had a technological advantage in that it operated in GSM, and when it started, all TeliaSonera's customers were still using NMT, an old analog technology. Tele2 grew quickly: During its first four years of operation, it gained 400,000 subscribers. In comparison, TeliaSonera had worked for nine years to achieve this number. No wonder TeliaSonera's executives were under stress. The business press from that period reports that TeliaSonera's management considered downsizing and layoffs. It was reasonable to predict that Tele2 would eventually become the market leader.

As we now know (and is apparent in Figure 1), this did not happen, and our results provide an explanation as to the reason. Could TeliaSonera's managers or market analysts have predicted the developing pattern? A way to do so would have been to examine the drivers of customer acqui-

sition for Tele2. If it followed cross-brand influence, Tele2's fast growth may not have been a good indicator for future competitive power; if growth was mostly at the within-brand level, it was possible that Tele2 differed enough to have been a threat from the beginning. A better understanding of the dynamics of within- and cross-brand communication could help here, as well as for many other firms.

In a general sense, this study is a first step in understanding the role and implications of within- and cross-brand influence for the marketing process. Although we focused here on the aggregate level, a natural next step is to examine the individual level. We also need to improve our knowledge of how social communications behavior and social network structure, such as weak and strong ties (Rindfleisch and Moorman 2002), affect this process. A promising avenue is that of agent-based models, such as cellular automata and small world (Goldenberg, Libai, and Muller 2001; Shaikh, Rangaswamy, and Balakrishnan 2006), which enable a more in-depth exploration of social processes and the way they aggregate to market phenomena.

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