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

Barak Libai
Recanati Graduate School of Business Administration
Tel Aviv University, Tel Aviv, Israel 69978
Sloan School of Management
MIT, Cambridge MA 02142
libai@mit.edu

Eitan Muller
Stern School of Business
New York University, New York, NY 10012
Recanati Graduate School of Business Administration
Tel Aviv University, Tel Aviv, Israel 69978
emuller@stern.nyu.edu

Renana Peres
School of Business Administration
Hebrew University of Jerusalem, Jerusalem, Israel 91905
peresren@mscc.huji.ac.il

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Abstract

Consumer-generated communication processes draw increasing attention of marketers and researchers. An under-researched issue, however, is that interpersonal communications is not always brand-specific. Hence, an individual can adopt a brand either as a result of communication with adopters of that brand (*within-brand influence*) or due to an interaction with adopters of competing brands (*cross-brand influence*).

This study shows that the interplay of within- and cross-brand influence can have a substantial effect on the growth of markets under competition. We develop a model that explicitly represents these two influences, and focus on the case of two otherwise-identical competing brands with differing entry times. Due to within-brand influence, current customers create an *interaction-based advantage* for the first entrant, which grows with time. Hence, we illustrate how customers should be viewed as market assets yielding increasing returns during the diffusion process. On the other hand, cross-brand influence enables a market follower to enjoy a shorter time-to-takeoff. Given the combination of both, we predict the “dual pattern” characterized by a fast takeoff for a follower, followed by a widening gap in favor of the first entrant, *ceteris paribus*. We show that such a pattern dominated the market growth of the cellular industry in Western Europe. We explain the reasons behind this dual pattern, rule out straightforward alternative explanations, and discuss the managerial implications.

Introduction

One of the major product introductions in the US in 2007 was the launch of iPhone by Apple. Observing the introduction closely, two key inferences can be drawn: First, the promotion of iPhone was heavily tilted toward word-of-mouth communications and buzz as opposed to paid advertising (Reuters 2007; 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). When observing the market's internal communication dynamics in this case, one might wonder to what extent this communication is specifically related to iPhone, and thus to what extent iPhone's competitors are enjoying the buzz generated by iPhone. While Apple is working under the assumption that interpersonal communication will help in pushing its own product, allowing it a relatively low investment in advertising, it appears that 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).

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

Following 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 Wind 2000; Mahajan, Muller, and Bass 1990). While some efforts have been invested in modeling diffusion at the brand level (Mahajan and Peterson 1978; Shankar, Carpenter, and Krishnamurthi 1998; Parker and Gatignon 1994; Krishnan, Bass, and Kumar 2000), the interplay among communications effects that stems from the brand's own customers vs. that of the competitors' customers has not yet been probed. In this study, we present a brand-level growth model that explicitly takes into account both within-brand and cross-brand influence, 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 differing time periods, a later entrant often enjoys a faster and sharper takeoff than that of the first entrant. The reason is that the follower benefits from the cross-brand influence from 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 has generally focused on the category level (Tellis, Stremersch, and Yin 2003; Golder and Tellis 1997). We show that besides the economical and cultural factors investigated so far, brand-level takeoff also depends on competitive position and communication dynamics in the market.

The "interaction-based advantage" of the first entrant: Due to within-brand influence, the customers acquired by the first entrant become a source of a self-reinforcing competitive advantage. Since at competition entry, the first entrant has more customers than a later entrant, it can expect more brand-specific interactions, and as a result, more new customers per period, which in their 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 *interaction-based advantage*. Given the above forces, the interplay of within-brand and cross-brand communications generates a *dual pattern* of growth, i.e., a faster takeoff of the follower, yet an increasing advantage to the first entrant, *ceteris paribus*. We show how the exact nature of this dual pattern depends on the relative strength of within-brand and cross-brand dynamics.

No need for perceptual difference: The focus on similar brands is central to our analysis, as it distinguishes the interaction-based advantage from previously identified sources of pioneering advantage and disadvantage that had been generally attributed to some perceived brand difference. In contrast, we show that even without any difference in perceived value among the brands, the within-brand 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. Note, however, that brands entering at differing 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: In order to empirically investigate the dual pattern, markets with relatively similar brands would help control for effects stemming from brand difference. We examined the cellular phone markets in Western Europe, wherein 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, straightforward alternatives such as differences in price, churn, and technology.

The rest of the paper is as follows: We first present the brand-level growth model, then demonstrate analytically the dual pattern. We next 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 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 paper is that the growth of a competitive brand can be affected by the interplay among sources of information for prospective adopters: the brand's own users, which provide within-brand effect; and the competitor's users, which provide 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.

Examining communication processes between adopters of a brand and prospective adopters, they can be classified into *brand-level* and *category-level* communications. The term "communication" may include word of mouth as well as other non-verbal imitation processes that are part of the contagion process associated with new products (Van den Bulte and Lilien 2001). Utility-related contagion such as network externalities, however, is not considered under communication, and will be discussed later.

Brand-level communication is specific to the characteristics of the brand. In the iPhone case, one would communicate about the specific virtues of iPhone. This phenomenon is typically presented in the business press to motivate managers to invest in their customers' satisfaction (Reichheld 2006; Pruden and Vavra 2004). 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 will be about the smart phone category. The research literature implies evidence of category-level effects generated by users of brands in the category. It was demonstrated that when relating to new products, consumers often use information on specific brands to generalize to other brands in the category, and also infer 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, it is often interpersonal communications that 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 regarding 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, Krishnamurthy, Prasad, and Sethi 2005; Chakravarti and Janiszewski 2004). Yet a similar investigation has not been conducted on differing types of interpersonal communications and their respective effects on market dynamics. Relevant behavioral research, however, suggests that communications effects work at both the category and 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-level and category level communications into within-brand and cross-brand influences can occur in multiple ways. Consider a user of brand *A* that communicates with a prospective adopter about the product. Usually, positive brand-level communication should lead to the purchase of the same brand. Brand-level communication can also lead to the eventual purchase of a competing brand *B*. This can happen in the case of category level communications, or alternatively in negative word of mouth. The latter case may be a less common case across categories, as 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 to the purchase of either *A* or *B*. Thus the decision to adopt brand *A* can occur due to both category- and brand-level communications, and brand *A* can gain users due to both its own users and the users of the competing brands.

Clearly, 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 a number of 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, wherein the consumer first adopts the category and then decides on the brand. Here, a nested Logit analysis may be called for.

Modeling the effect of within-brand 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, however, is to assume that each brand has its own unique market potential such as in the pioneering work of Peterson and Mahajan (1978), as well as some later works (Mahajan, Sharma, and Buzzell 1993; Shankar, Carpenter, and Krishnamurthy 1998). This assumption may fit a case wherein brands differ so widely that they focus on discrete consumer pools, yet is less suited to the case of similar brands in the same category.

While 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; we thus 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
q_{ij} - Cross-brand influence of brand j on brand i

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

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

Adopters of brand i (N_i) spread brand-level communications by contacting and converting non-adopters $(m - N)$ at a rate of q_i to adopt brand i. In addition, due to cross-brand influence, adopters of the competing brands j contact and convert non-adopters $(m - N)$ to adopt brand i at a rate of q_{ij}. Hence, 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 the brands j. Note also that consistent with most of the diffusion literature, we do not explicitly model negative word-of-mouth if it exists, but rather regard the overall resulting 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, within-brand influence is equal to cross-brand influence, the model is that presented by Krishnan, Bass, and Kumar (2000); 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). Their underlying assumption is that there is no relevance to the brand ownership of the individual who spreads the communications. If, however, $q_{ij} = 0$, then only within-brand influence is present, and the model is similar to that presented in Kalish, Mahajan, and Muller (1995); another model by Parker and Gatignon (1994); and Mahajan, Sharma, and Buzzell (1993). In most cases, however, one can expect both cross-brand and within-brand influences, and that their respective magnitudes are not necessarily 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, Differing Entry Times

The model of 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, well illustrates the differential effects of cross- and within-brand influence on market growth. Clearly, competitive dynamics themselves may generate a perceptual difference in the two brands, either because of an actual difference, or due to 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). Since we wish 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 to each other in both their product- and brand-related attributes, hence we assume that $q_i = q_j = q$ and $q_{ij} = q_{ji}$ $p_i = p_j$

Without loss of generality, we assume that Firm i was first to market, and 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 since we know that the category-level solution is a Bass function, the model can be solved analytically to yield the following for $p_i = p_j$ (see Appendix 1 for the more general case where $p_i \neq p_j$):

$$(2) \qquad N_k(t) = (m/2)\frac{S - e^{-(P+Q)t}}{S + (Q/P)e^{-(P+Q)t}} + (-1)^{k+1} m \frac{\left(S + Q/P\right)^{\alpha-1}(S-1)/2}{\left(S + (Q/P)e^{-(P+Q)t}\right)^{\alpha}}$$

Where *k* receives the value of 1 for the pioneer and 2 for the follower, $P = p_i + p_j$; $Q = q + q_{ij}$; $S = \dfrac{m + (Q/P)N_0}{m - N_0}$; $\alpha = \dfrac{q - q_{ij}}{q + q_{ij}}$

The first term of Equation (2) is the Bass function with non-zero initial condition. Parameter *S* represents the effect of the additional initial seed of adopters, termed the *seeding factor* by Muller, Peres, and Mahajan (2007). The second part of Equation (2) is added to the first entrant and subtracted from the follower, representing the asymmetry in initial conditions. Summing up Equation (2) for both firms, yields the Bass equation with non-zero 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 number of customers between the first entrant and the late entrant, or $N_i(t) - N_j(t)$. To see how the gap changes with time, we take the derivative of the difference between the number of customers of the first entrant and the follower. Based on Equation (1), we get

$$\text{(3)} \qquad \frac{dN_i(t)}{dt} - \frac{dN_j(t)}{dt} = (q - q_{ij})(N_i(t) - N_j(t))(m - N(t))$$

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:

> **Proposition 1.** When within-brand communication is more intense than that of cross-brand influence ($q > q_{ij}$), the gap between the first entrant and the follower will grow over time.

Since, as discussed before, it is expected that in actual markets, and in the presence of positive communications, within-brand communication is indeed more intense than that of cross-brand influence, we expect that the growing gap will prevail 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, let us look at 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 favoring first entrant and cross-brand communications, which assist the follower. Since the within-brand is stronger than the cross-brand, the first entrant, who initially has more customers, will acquire more new customers in subsequent periods - customers who in turn disseminate communications - in turn reinforcing the initial advantage. Thus, the initial bulk of N_0 customers forms an increasing return asset to the first entrant.

The dual pattern

In order to describe the full pattern of competitive growth under communications effects, we need to not only examine the dynamics of adoption over time, but we also need to examine the point of entry of the follower. Thus, we examine the initial rate of adoption for the follower, and compare it to that of 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 time of competition entry. A straightforward computation shows that if $p < q_{ij}(1-N_0/m)$, then 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 is lower than that of cross-brand influence. While empirical past data on cross-brand communications is not available, our empirical analysis suggests that the level of cross brand internal effect (q_{ij}) is on average stronger than that of external influence for the follower (p_j). In a more general sense, diffusion internal influence parameters have been found to be considerably larger than external influence ones (Mahajan, Muller and Wind 2000). Thus this outcome is not unexpected.

The second condition is that the follower enters 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 competition entered (Srinivasan, Lilien, and Rangaswamy 2004; Golder and Tellis 1993).

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

> **Proposition 2.** If cross-brand communications influence is stronger than that of 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, notice that when the follower enters the market, two forces initially shape its growth compared to the first entrant: On the one hand, the follower can enjoy cross-brand influence from the first entrant, an advantage over the first entrant, who 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, thereby diminishing the effect of both cross-brand and within-brand influences. So, if cross-brand influence is strong enough, and entry is early enough, initial adoption rate for the follower is higher.

From Propositions 2 and 1, we see that when the follower enters the market early enough, we can expect to see a pattern of initial high growth for the follower, yet a growing gap in favor of the first entrant, *ceteris paribus*. 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, as 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 pointed to may be just one source of advantage or disadvantage of market players. There are numerous examples in which pioneers did not survive in the long run, or at least lost their market leadership (Srinivasan, Lilien, and Rangaswamy 2004; Golder and Tellis 1993) 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 focused on markets for similar brands to be able to 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 be different, 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 on latecomer's eventual market leadership (Golder and Tellis 1993).

Yet, to become the market leader, or at least close the gap, a superior latecomer has to overcome the interaction-based advantage that still exists due to the within-brand effect of the pioneer. How large should the perceived quality difference be in order for the follower to overcome the interaction-based advantage of the pioneer? While this question cannot be answered analytically, we can simulate the growth process based on Equation 1 to find out the answer numerically (see Appendix 2). With the average parameters obtained in our empirical analysis (to be described shortly), the growth parameters of the followers had 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:

> **Proposition 3.** The growth parameters of the newcomer (*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 with the pioneer.

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 where brands are similar. This analysis is comprised of 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 see how they comply with the conditions stated in the formal analysis. Then,

[1] We 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 in order 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 to be 30). This is a conservative choice, since 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 had 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. See Appendix 2 for details.

we test whether there is an empirical association between cross- and within-brand influences, and the growth of the gap over time, while testing 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, where data are readily available. Second, data quality problems arise in the early growth of the product life cycle (Golder and Tellis 1993). For example, due to the use of survey data in retrospect, successful late entrants that were not actually the first entrants were considered to be so, while failed pioneering efforts were not considered (Hauser, Tellis, and Griffin 2006). Finally, we sought to investigate a market where brands are similar in order to control for other factors that may create noise in the data.

We were able to obtain a high quality brand-level growth database for the European cellular service industry. Cellular markets are both relatively new and highly documented. Hence they have been used for analysis of market growth focusing 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). In fact, due to 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, and so provide adequate data for examining pre- and post-competition 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 US, wherein the cellular market is fragmented and composed of a number of service providers, in Western Europe, each a of a small number of competitors enjoyed full coverage of their respective countries, making the competition structure straightforward.

Importantly, this industry has been regulated, leading to two favorable consequences for our purposes. First, the cellular industry began it 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 started and when others joined. In addition, market entry of the follower can be treated as an exogenous factor, as in our model. Also, due to regulation, many operational aspects of the firms were monitored and controlled in order 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 phone 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 1st of each year. We excluded minor markets such as Andorra, Monaco, and Luxembourg, and also Greece, where the competitive structure was breached early on due to mergers of operators. The data are provided by the World Cellular Information Service (WCIS) database, which is widely used in the cellular industry and contains subscriber data, as well as some operational data. We also searched the relevant business press in order 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 average monopoly time 7.8 years. The number of service providers ranged between two and five per country. The first two entrants in the country occupy, on average, 78.7% of the market share. Therefore, to be consistent with the focus of the model presented above, and in order to keep the analysis simple, we focused in each country on the first two entrants.

One exception to the above is the UK, 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 rest of the countries, we still analyze the first two firms in the UK, but note that the case of the UK may not fit our approach well. In three countries - Ireland, Sweden, and the UK - the original first entrants did not take off, mainly due to lack of investments by the service provider (in the UK, for example, British Telecom was awarded the license, yet eventually decided not to invest resources in mobile telephony). Hence, for these countries, we considered the first entrant to be the first service provider that took off. Table 1 provides a list of the cases we used:

- insert Table 1 around here -

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.

- insert Figure 1 around here -

Looking first at the early growth of the later entrant (Proposition 2), we compared the time to takeoff of both the first entrant and later entrant. To identify takeoff, we used the threshold approach of Tellis, Stremersch, and Yin (2003). Table 1 presents the takeoff points for the firms in our data set, from which the following result could be ascertained:

> **Result 1**: The time to takeoff of the late entrant is significantly shorter than the time to takeoff of the first entrant. While average time to takeoff of the first entrants was 8.1 years, average time to takeoff for the second entrants was only 2.9 years.

It is clear that other factors may affect a second entrant's rapid takeoff, such as the overall tendency of takeoff to shorten over the years (Tellis, Stremersch, and Yin 2003). One way to still consider this phenomenon in the context of our model is to look at the existing penetration of the pioneering brand. Our formal analysis (see Proposition 2) shows that if market penetration at 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 via cross-brand communications. Hence we can expect that 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%; therefore we expect the correlation to hold up. Indeed, the Pearson correlation between time to takeoff and the first entrant's penetration rate at competition entry is $r = -0.46$ (p = 0.07).

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.

The second 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; whereas if both communication types are equal, then 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 second entrant for each period *t* since the competitive entry. In order 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, we performed for each country *y* a regression of this difference over time: $gap_{yt} = \alpha_{0y}+\alpha_{1y}t+\varepsilon_y$. The slope α_{1y} of the change can serve as an indicator of the widening of the gap, and is our measure for the gap widening rate. Table 2 presents the results of this measurement for all the countries in our data set. We see that in 12 out of the 16 countries, the slope is positive, i.e., the gap increases over time. In four countries, it is not significantly different from zero ($p > 0.05$). In none of the countries does the gap decrease significantly over time. These results comply with an intuitive look at the data in Figure 1 for all the countries except Germany.[2]

- insert Table 2 around here -

Result 3: The gap in the number of subscribers between the first entrant and the follower either increases on average over time (12 out of 16 countries), or remains constant on average (4 out of 16 countries). In none of the countries was an average decrease of the gap observed.

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

The magnitude of cross-brand and within-brand effects

Our next step is to obtain measurements of the cross-brand and within-brand influences. We used Equation (1) for the first and second entrant in each country, and as in the formal analysis assumed that $q_i = q_j = q$, and $q_{ij} = q_{ji}$. 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, thereby reflecting the capacity of brands to affect consumers through their promotional activities. For each country, the penetration curves were estimated simultaneously, using Seemingly Unrelated Regression (PROC MODEL in SAS). Table 3 presents the parameter values.

- insert Table 3 around here -

From Table 3, we see that for all the countries except Germany cross-brand influence is weaker than within-brand influence ($q_{ij} < q$). The average $q_{ij} : q$ ratio is 0.55. That is, as one could logically expect, 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 higher chances of the consumer acquiring that brand. This result illustrates the importance of explicit representation of within-brand and cross-brand influences: Regarding the two influences as equal leads to overestimation of the cross-brand influence and underestimation of the within-brand influence, a bias which might harm the fit and forecasting.

Other Forces at Play

While our basic analysis that explored the dual pattern assumed similar brands, 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 wish to consider some of the major alternative factors that might serve as explanations for the dual pattern in the markets we analyzed, and compare them to the communications explanation.

1. Price difference (PriceDiff) **–** Prices can have significant influence on market evolution. A first entrant's ability to sharply reduce price enables it to draw more customers and open up a gap. Our data set contains quarterly price data (for most quarters) for a minute in peak airtime, in US dollar nominal values, since 1993 (no price data is available for most of the current decade, wherein the database managers stopped assessing average price due to the growing complexity of the plans). In cases where competition started after 1993, we used data from the competition's start. 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 second entrants.

While the value of PriceDiff will be presently used in a multivariate analysis, even an initial analysis of the data suggests that price may not be a good explanation for the gap. Out of the 16 countries whose data we studied, in only two was the average price of the first entrant lower than the average price of the follower. If anything, PriceDiff should have helped to close the gap, not open it. To further examine this point, we used the Generalized Bass Model (GBM - Bass, Krishnan and Jain 1994). Equation (4) is therefore the GBM extension of Equation (1), where *f* is some decreasing function of price:

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

In order to apply the new model to the data, we extrapolated for the years where no price data were available using exponential function, and applied a linear effectiveness function *f* in Equation (4). Out of the 12 countries where the model converged, in seven the price coefficient was not significant, while in the five significant ones, the coefficient had the right (negative) sign. In order 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 five countries wherein price was significant have five parameters each (two each for p and q and one for the market potential). Out of these 25 parameters, 24 have not changed (at the 5% significance level).

2. 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 impact 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, since they create an increasing return mechanism based on number of customers, which may be hard to distinguish empirically from the communications effects on which we focus.

While distinguishing between the two is indeed non-trivial, a few issues should be taken into account: First, network effects should indeed help bolster the market leader. Hence in a network effects-dominated scenario, the follower would have a hard time initially taking off. However, this is not consistent with the fast follower takeoff that we actually see. 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 number of subscribers captures network effect in our case is questionable. Birke and Swann (2006), for example, studied the cellular market in the UK and concluded that while 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 (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 UK cellular market. They found that while consumers were generally aware of market competitors, they were confused regarding not only the difference between them, but also regarding competitors' exact roles or positions within the structure of the industry. Interestingly, Turnbull, Leek and Ying also found 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, since 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 very dominating role in the growth of these markets.

3. Churn difference **(**ChurnDiff) – Churn, or customer defection, 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. Note, however, that since the follower starts with considerably fewer customers, the difference between the churn rates of the two must be very large in order to explain a big 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 since the data are not complete and do not enable a quarter-by-quarter pair comparison.

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

To further examine the effect of churn, we corrected the number of new customers each period taking into account churn, following a similar approach by Gupta, Lehmann, and Stuart (2004). Assume that at time *t*, the ***observed*** net difference 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 by 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. Hence:

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

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

Since we have the observed number of adopters and know the churn rate, we can retrieve the actual number of adopters. In order to apply the new model to the data, we extrapolated for the years wherein no churn data were available. Note that given the rather similar churn rates we observed in our data, since the pioneer had more customers initially, its loss from churn is larger than that of the follower. Thus, following the approach presented here, in order to get the observed widening gap, the interaction-based advantage should by even higher, as the pioneer has to overcome the churn. This is indeed what we get from an empirical analysis, compensated for churn, as is demonstrated in Table 4.

- insert Table 4 around here -

4. Technology (%GSM) - Pioneering advantage or disadvantage can be a function of the technologies used by the various market players. In our case, however, the advantage lay with the follower. The "technology vintage effect" indicates pioneering disadvantage wherein the later entrant utilizes 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 started gradually moving over to digital technologies. The second entrants, on the other hand, entered offering all digital technology (GSM), which was considered superior, and to which the entire European market eventually moved.

To be able to quantify and see possible technological differences between 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 the difference among the competitors.

5. Control of infrastructures (Penetration) – Another source of pioneering advantage may be the control of resources that 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 before that the penetration level of the first entrant at the follower's entry helps the follower to initially reach takeoff. However, this penetration level can also serve as a proxy to the control of infrastructures, and therefore as an aid to first entrant advantage. The **Penetration** variable to be used is thus 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 was opened 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%.

6. Number portability (N-Portability)– One of the barriers 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 of the

European countries implemented this change before the 2002 directive, while 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 (Smura 2004 and ECC 2005). We operationalize this variable by measuring in each country the time it took (in months) from the introduction of cellular service to implementation of number portability.

We next examine the extent to which a communications pattern helps explain the gap in customers, compared to other factors we could quantify. The dependent variable is the gap between the first entrant and follower, for which we will use the gap-widening rate calculated in Table 2. For the independent communications parameter, we used the q_{ij} / q ratio, or the ratio between the cross-brand and within-brand influences. As Result 2 indicates, the stronger the within-brand effect compared to the cross-brand effect, the more the widening gap favors the first entrant. Hence, we expect that this variable's coefficients will be negative, i.e., the weaker the cross-brand influence relative to the within-brand, the higher the widening rate of the gap. Additional independent variables are price difference, churn difference, penetration level of the first entrant at 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 are presented in Table 5:

- insert Table 5 around here -

From Table 5, we see that the only significant variable is q_{ij} / q . As expected, the coefficient is negative, that is, the weaker the cross-brand effect relative to the within-brand, 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. In order to further validate this result, we conducted an additional test: In the above analyses, we used as a dependent variable the measurements of the gap widening rate presented in Table 2. Hence, we performed a two-stage process: first a computation of the gap widening rate, and then a test of 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*), then the combined model is:

$$(6) \qquad gap_t = \alpha_{01} d_1 + \alpha_{02} d_2 + ... + \alpha_{0Y} d_Y + (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k)\ t + \varepsilon$$

Excluding again the outlier of Germany, the regression results imply that, as in the previous analysis, the q_{ij} / q ratio is significant. An additional interesting source of influence found to be 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 *%SGM* is an indication of technological difference, or the level of technological substitution: Its sign is positive, i.e., the higher the number of first entrant subscribers who already switched to GSM at competition entry, the lower 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 to previously available models of brand growth. We compare three models, which represent three approaches regarding brand-level diffusion and the communication effect: The first is the model by Krishnan, Bass, and Kumar (2000) (KBK) wherein 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) wherein the communications influence is within-brand only. The third model is the one presented here that allows within-brand and cross-brand influence.

(7) KBK $$\frac{dN_i}{dt} = (p_i + \frac{q_i(N_i + N_j)}{m}) \cdot (m - N_i - N_j)$$

(8) KMM $$\frac{dN_i}{dt} = (p_i + \frac{q_i N_i}{m}) \cdot (m - N_i - N_j)$$

(9) Current Model (CM) $$\frac{dN_i}{dt} = (p_i + \frac{q_i N_i}{m} + \frac{q_{ij} N_j}{m}) \cdot (m - N_i - N_j)$$

We first conducted a straightforward fit comparison of the three models. In order to meaningfully compare the models, we set the same number of parameters in each model by assuming in the present model that $q_i = q_j$, $q_{ij} = q_{ji}$. 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. Neither did the three models differ in their forecasting abilities using two step-ahead predictions.

The advantage of the CM model is captured in the less restricted description of the mechanism that drives brand-level growth. Specifically, in order to fit as well, the other two models must make assumptions that may not be robust, and are unnecessary under our more general approach. First note that in its full version, the CM model is a generalization of KMM and KBK, i.e., KMM is the special case wherein $q_{ij} = 0$, and KBK is the case wherein $q_i = q_{ij}$. The CM model provides the required flexibility for describing both within-brand and cross-brand influences and hence the dual pattern. Take for example the growth curves in the case of identical brands ($q_i = q_j$, $q_{ij} = q_{jj}$, and $p_i = p_j$): The KBK 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 long time to takeoff 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 in order to obtain this pattern.

When the brands are not identical, any growth pattern can be generated, and specifically both KMM and KBK can generate the dual pattern. However in order 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 for generating 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, since the follower does not receive any cross-brand word of mouth, its growth is very slow; therefore the follower needs to have higher q and p in order 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, hence one might suspect 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

Though 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. One could wonder to what extent additional entrants would 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 of course the third entrant is dissimilar, introducing a superior product that will draw adopters to it. While obtaining a closed form analytical solution for the case of more than two players has proven to be non-trivial, simulations we conducted for the case of similar brands indicate that this is indeed the case. Also, our data are generally consistent with a disadvantage for further entrants. In the cellular markets we analyzed, the first two entrants captured close to 80% of the market, and in only one case of the 16 has the third entrant overtaken one of the first two. These cases, at least, 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 results that are similar to the two-player case in terms of both their R-Squares and their implications: In all the cases, except for that of the UK, 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 from the authors).

Discussion

The results of this study can be summarized 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).
- Due to the cross-brand effect, in a market that exhibits differential entry by similar brands, the follower will often enjoy a shorter time-to-takeoff compared to that of the pioneer.
- However, the pioneer may enjoy an "interaction-based advantage" due to within-brands effect, i.e., an increasing return mechanism by which it can acquire more new customers due to 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 of the factors that eventually will create the differential sales pattern. However, to overcome the interaction-based advantage, consumer perception of the follower has to be considerably better than that of the pioneer.
- We label the combination of a fast takeoff for the follower, yet an overall growing gap in favor of the pioneer the *dual pattern*. In the Western European cellular market, the dual pattern prevails in 14 of 16 countries. The communication approach provided a better explanation than other straightforward alternative explanations.

Our approach follows the growing interest of academic marketing researchers in brand-level diffusion (Krishnan, Bass, and Kumar 2000; Shankar, Carpenter, and Krishnamurthi 1998;

Parker and Gatignon 1994; Peterson and Mahajan 1978), yet it differentiates between the various types of customer communication. Our results indicate that the distinction between the types of communication is important, and encourage future modelers of brand level to further study the consequences of this distinction.

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., Srinivasan, Lilien, and Rangaswamy 2004; Kalyanaram, Robinson, and Urban 1995; Golder and Tellis 1993). 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, as 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, i.e., the more intense the brand-level communications, the greater the advantage; while the advantage declines with increasing category-level (and hence, cross-brand) communications.

Finally, interaction-based advantage is an increasing return phenomenon, in contrast to most perception-based advantages that may fade as the later entrant becomes established in the market. This complements previous writings on increasing returns in the product growth process that 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, since it is not restricted to specific product markets. It is also consistent with the work of Arthur (1994), who suggested that increasing return processes may dominate much of the economy and can be a byproduct of human interactions in general.

Brand level takeoff

As detailed in Proposition 2, in many cases of similar brands, the takeoff of the follower is faster than that of the earlier entrants. This insight provides an interesting contribution to the growing literature on new product takeoff. Takeoff patterns have up to now 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 inter-country effect (Golder and Tellis, 1997, 2004; Stremersch and Tellis, 2004; Tellis, Stremersch, and Yin, 2003). Yet the interest of managers probably also includes the brand level and not only the category one.

If we look at 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. In fact, if the first entrant is a monopoly for long enough, its takeoff will be the category takeoff. For the later entrants, that takeoff should be not only a function of the category-level factors (and for non-similar 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 pioneer's customers in the market may help the new entrant's takeoff, and not the opposite.

The cross-brand effect has an additional interesting implication. Recent research has called for customer profitability research to take into account the value of the internal dynamics among customers (Gupta et al 2006). Through 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. Hence, 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

While dual pattern should be more easily recognized in markets for similar brands, the forces we identify ought to be at work regardless of brand similarity. To what extent one should expect in general a dual pattern in competitive growth markets? This question is especially relevant as both empirical and conceptual work point to the possible advantage and eventual success of late entrants to markets, (Hauser, Tellis, and Griffin 2006). We see two issues that determine the relevancy of the dual pattern across markets:

a) The power of brand-level communication: In some markets, brand-level communication may not be a strong force that drives adoption. For example:

- *Fast-moving consumer goods* (FMCG). Diffusion theory is less relevant to the growth of fast-moving consumer goods, which are typically not as new or as risky as are technological products. Interestingly, empirical findings suggest that FMCG markets may indeed differ regarding pioneering advantage compared to 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. Hence, cross-brand communications, followed by brand-level marketing mix, will dominate.

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

It should be stressed 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 cross-brand and within-brand influences, especially when one considers that it is well established that social contagion considerably impacts physician decision-making (Bhatia, Manchanda, and Nair 2006). However, in some drug markets, later drug entrants may be more innovative (Shankar, Carpenter, and Krishnamurthy 1998), which should reduce the interaction-based advantage. One might think that the entry of generics may be a good example for our case, because the new brand is so similar in term of ingredients. Yet decisions on adoption of a generic drug may be made less by physicians and more by HMOs that will 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 where brands compete for a standard are an interesting variation on the framework we presented, since often the competing brands may be similar in most attributes, and the difference among them stems 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 question is the nature of this effect at the brand level. While our model would not capture the phenomenon of potential adopters waiting to adopt to see “who the winner is”, when they do adopt, we expect network externalities to complement the within-brand effect, and amplify the increasing return phenomenon. On the other hand, they will work against the takeoff of the follower. There is no “cross-brand” equivalent in the case of network effects, and probably the lower utility due to fewer users of the standard will impact the follower’s adoption parameters and hence we may not see a dual pattern.

Managerial implications

The distinction between cross-brand and within-brand effects on growth bears some significant managerial implications. First, one needs to draw the distinction between the two when conducting market research. Recently managers have become increasingly aware of the need to research and even aim to affect interpersonal communications such as word of mouth, as well as the fact 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 the conventional wisdom focuses only on within-brand influence. In order to fully realize the difference between the two types of communication effects, 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 are observing their own brand as well as that of the competition, as well as to other stakeholders such as market analysts. First, controlling for other factors, the shorter time-to-takeoff of a second entrant should not be surprising. Because takeoff is used by managers as an important sign of the health of a brand (Golder and Tellis 1997), the shorter time-to-takeoff 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. Hence other perception- based measures are probably needed to indicate if a second brand's shorter time-to-takeoff 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, from 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. Tele2, on the other hand, 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 of TeliaSonera's customers were still using NMT, an old analog technology. Tele2 grew very 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 began to feel stressed. The business press from that period reports that TeliaSonera's management started to consider downsizing and layoffs. It was reasonable to predict that eventually Tele2 would become the market leader.

As we now know (and can be sees 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? One way to do so would have been to examine the drivers of customer acquisition for Tele2. If it followed cross-brand influence, then Tele2's fast growth may not have been a good indicator for future competitive power; if growth was mostly at the within-brand level, then was possible that Tele2 differed enough to have been a threat from the beginning. Clearly, a better understanding of the dynamics of within and cross brand communication could help much here, as well as for many other firms.

In a more general sense, we see this study as a first step in our understanding of the role and implications of within- and cross-brand influence for the marketing process. While we focused here on the aggregate level, a natural next step is to move toward 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 2001) - affect this process. A promising avenue is that of agent-based models such as cellular automata and small world (Shaikh, Rangaswamy, and Balakrishnan 2006; Goldenberg, Libai, and Muller 2001), which enable a more in-depth exploration of social processes and the way they aggregate to market phenomena.

Table 1: Cellular Service Providers and their Time to Takeoff

	First Entrant			**Second Entrant**		
country	Operator	Year of Entry	Time to Takeoff (years)	Operator	Year of Entry	Time to Takeoff (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
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
UK	Vodafone	1985	8	T–mobile	1993	6
Average Time to Takeoff			8.1			2.9

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	0.0140	0.0005	Increase
Belgium	0.0197	0.0082	Increase
Denmark	0.0157	0.0000	Increase
Finland	0.0133	0.0043	Increase
France	0.0104	0.0000	Increase
Germany	0.0050	0.0055	Increase
Iceland	0.0074	0.0758	Constant
Ireland	0.0114	0.0219	Increase
Italy	0.0032	0.2450	Constant
Netherlands	0.0282	0.0001	Increase
Norway	0.0196	0.0001	Increase
Portugal	0.0212	0.0000	Increase
Spain	0.0344	0.0003	Increase
Sweden	-0.0001	0.9469	Constant
Switzerland	0.0322	0.0014	Increase
UK	-0.0081	0.0430	Constant

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	0.5924*	0.4423*	0.747	5,257,091*	0.922	0.867
Belgium	0	0.0083	0.824*	0.1372	0.167	6,859,488*	0.924	0.832
Denmark	0.0023	0.0112*	0.3157*	0	0.000	4,429,937*	0.437	0.502
Finland	0	0	0.4234*	0.1667*	0.394	4,174,702*	0.709	0.193
France	0.0013	0.0031	0.7051*	0.0174	0.025	36,563,972*	0.797	0.777
Germany	0.0024	0	0.1969	0.7183*	3.648	52,182,828*	0.69	0.498
Iceland	0	0.0027	0.4562*	0.2584*	0.566	293,597*	0.777	0.917
Ireland	0.0114	0.0316*	0.7163*	0	0.000	3,546,547*	0.557	0.765
Italy	0.0057	0	0.4086*	0.2899*	0.709	47,632,623*	0.751	0.844
Netherlands	0	0	0.6563*	0.3174*	0.484	8,527,233*	0.203	0.757
Norway	0.0028	0.0089	0.2949*	0.0496	0.168	4,906,969*	0.257	0.699
Portugal	0.0079	0.0026	0.6405*	0	0.000	8,567,577*	0.876	0.41
Spain	0.0006	0.0097	0.8392*	0	0.000	28,867,446*	0.871	0.306
Sweden	0.0015	0	0.2262*	0.1764*	0.780	8,417,699*	0.586	0.853
Switzerland	0.0003	0.0045	0.5457*	0.1775*	0.325	5,239,988*	0.713	0.659
UK	0	0	0.4078*	0.3472*	0.851	29,164,818*	0.31	0.82

Table 4: The gap widening rate estimation for observed and churn-compensated data

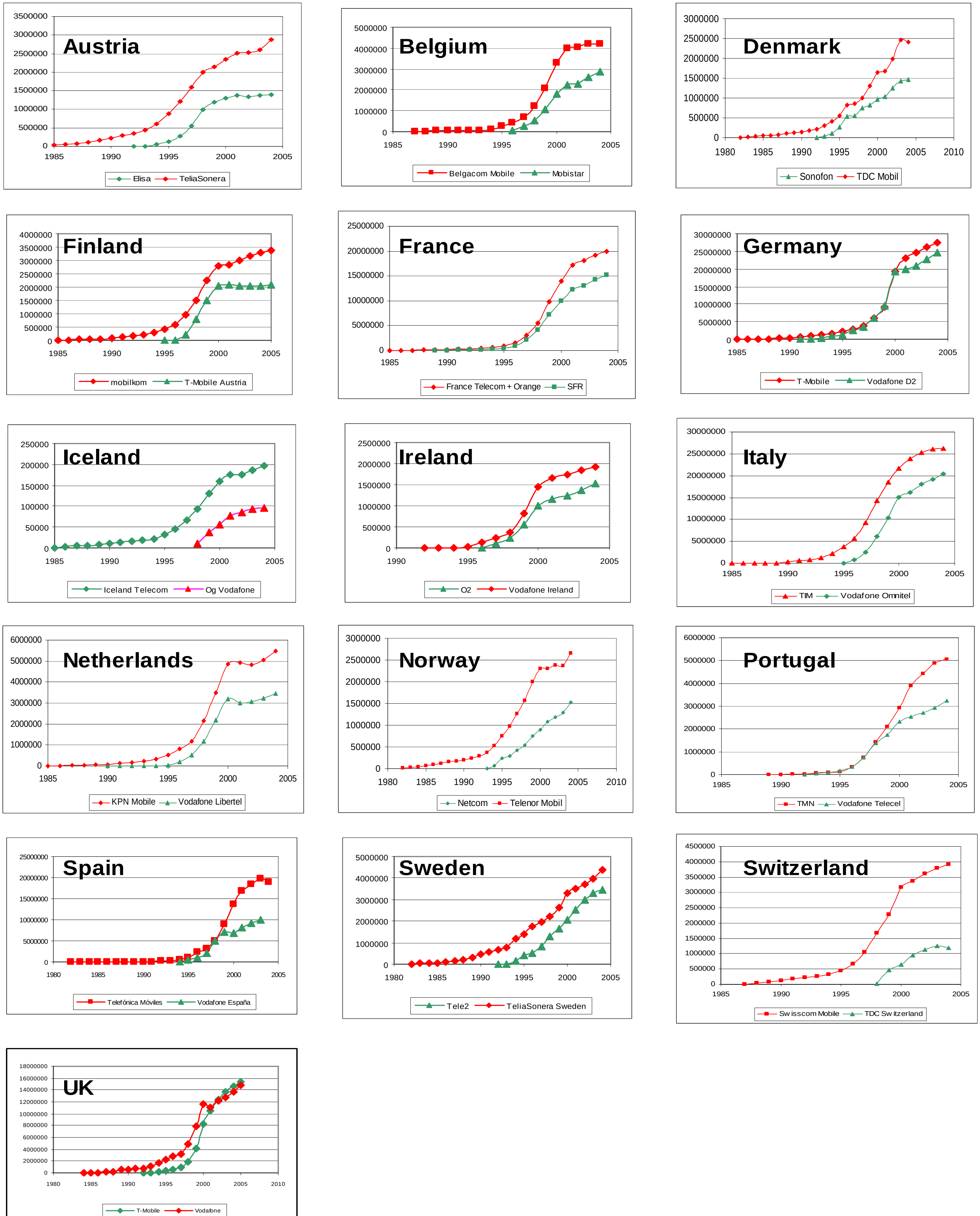
Country	Gap widening rate on observed data	Gap widening rate on compensated data
Austria	0.0140	0.0533
Belgium	0.0197	0.0927
Denmark	0.0157	0.0644
Finland	0.0133	0.2151
France	0.0104	0.0251
Germany	0.0050	0.0122
Iceland	0.0074	0.1576
Ireland	0.0114	0.0609
Italy	0.0032	0.0223
Netherlands	0.0282	0.0518
Norway	0.0196	0.0324
Portugal	0.0212	0.0460
Spain	0.0344	0.0802
Sweden	-0.0001	0.1334
Switzerland	0.0322	0.0972
UK	-0.0081	0.0296

Table 5: Other influences on the widening gap: A two-stage process

Parameter	Estimate	P-value
Intercept	0.02226*	0.0297
q_{ij} / q	-0.02993*	0.0620
ChurnDiff	0.07593	0.7572
PriceDiff	0.01060	0.8601
Penetration	-0.01134	0.8687
% GSM	0.02708	0.1161
N-portability	-0.00003	0.8421

The variables q_{ij}/q represents the ratio of cross-brand to within-brand influences, while *ChurnDiff* and *PriceDiff* are the average difference in churn and price between the pioneer and follower. *Penetration* and *% GSM* is 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.
* significant at $p < 0.1$, $R^2 = 79\%$

Figure 1: The dual pattern of follower's initial fast growth and first entrant's increasing later gap:



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