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2013/96/MKT

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August 15, 2013

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Abstract

Our objective is to empirically assess how competitive marketing effort and market growth, in terms of sales volume, interact. Researchers are acutely aware of the relationship between marketing expenditures and market growth yet this relationship has not been formally tested nor has the possibility of changes in the dynamics of this relationship over the course of market evolution been considered. Using a set of data on the sales and spending of 3 pharmaceutical categories across 7 countries, we analyze this relationship over the evolution of these categories from the introductory stage of the product life cycle to the maturity stage. An econometric hierarchical linear model is developed to represent the nature of the data. We find strong evidence that the breadth of marketing spending moderates the relationship between marketing spending and sales growth and that it changes over the course of the category life cycle. In particular, higher breadth in marketing expenditures when the market has few competitors arrest market growth whereas higher breadth when the market has many competitors fuels market growth. A further insight provided by the analysis shows that, beyond market share effects, the "cancelling out" of marketing spending increases as a category matures and this weakens the relationship between marketing spending and market growth.

Key Words: market evolution, market growth, marketing breadth, market maturity, introductory stage, entry deterrence.

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1 Introduction

Market growth and competitive dynamics are key elements to understand business and marketing strategy. While each topic has generated an extensive stream of research, these have evolved independently. Market growth has spurred extensive work on diffusion modelling. Competitive dynamics forms the basis for economic and econometric studies that elucidate how firms interact with each other. The problem is that market growth is inextricably linked to competitive dynamics yet links between the two areas have largely been ignored (Lambkin and Day 1989, Gatignon and Soberman 2002). Accordingly, it is imperative for marketing researchers to examine these links and to identify the implications these links have for managers (Soberman and Gatignon 2005). The objective of this study is to investigate the role played by the characteristics of competitive marketing spending as determinants of market growth. The evolution of this role from the introductory stage to market maturity is analyzed. In particular, we seek to understand 1) how market growth is influenced by the extent to which spending is spread across different marketing elements, 2) the extent of cancelling-out effects when the marketing spending becomes more concentrated, and 3) whether the influence of these factors (marketing spending breadth and concentration) on the relationship between marketing spending and market growth depend on the number of competitors in the product category.

The intent of this paper is not to delve into the vast research of how the nature of competition evolves as a category matures through the product life cycle. The majority of that research focuses on competitive entry and exit in the context of product category sales and diffusion. The number of competing firms indirectly affects demand for a product through its influence on product development, promotion, and pricing (Horsky and Simon 1983; Parker and Gatignon 1994). In fact, Kim , Bridges and Srivastava (1999) include the number of competitors as a source of variation in the parameters of a diffusion model over time. Horsky (1990) considers the relationship between product benefits and market evolution and Cestre and Darmon (1998) study the relationship between consumer preferences and new product diffusion. Collectively these papers suggest that product improvements in attributes have a significant impact on the diffusion rate.

However, few studies have examined the impact of competitive marketing expenditures on the growth of the market. The evolution of product category sales has been analyzed in the diffusion literature, with and without using total category marketing effort as explanatory variable (Bass 1969a, b, Van den Bulte and Lilien 2001). However, these approaches do not account for the manner in which the various competitors use their marketing instruments. One obvious reason is the lack of data. To understand the long term impact of competitive market spending, one needs data for each brand from the beginning of a category to its maturity stage. Another reason is the possible endogeneity between marketing spending and the maturity of a category (Bronnenberg, Mahajan and Vanhonacker 2000). Our approach to studying this question is to build a model at the market (category) level, where the breadth of marketing spending and the degree of competitive concentration moderate the relationship between total marketing spending and category growth. We find that broader marketing spending can either increase or decrease the growth of the market, depending on the number of competitors in the market place. More specifically, when there are only a few firms in the market, broader spending is primarily utilized to deter potential entry, thus the market grows more slowly. When there are many competitors, collusion is difficult and broader spending serves to inform potential consumers in all possible means, resulting in an increase in growth. We also examine the impact of competitive concentration on market growth, i.e., will the growth slow down when the marketing expenditures are concentrated: the expenditures comes from a few firms. Our finding suggests that such impact is negative, i.e., concentrated expenditure decreases the market growth rate. However, it is moderated by the total level of spending in the market.

The paper is organized as follows. In the next section, we draw theories and empirical findings from a variety of related studies and develop our hypotheses, followed by a description of our data. We then construct a model to address these hypotheses. In section 5, we provide the estimation results and robustness check. The paper concludes with a broader discussion of related issues.

2 Conceptual Framework

The key variable of interest in our study is the speed of evolution in the size of a market. Extant research has demonstrated the impact of investments in marketing as well as the role of the number of entrants in a product category (Parker and Gatignon 1994, Milgrom and Roberts 1982, Lane 1980, Schmalensee 1989, 1978, 1974). However, little research has focused on the way the players invest their marketing budgets and how these decisions influence market growth at different stages of the competitive context. We focus on two aspects of the competitive spending that have been identified in the literature: (1) the breadth of use of marketing instruments by the competitors and (2) the concentration of the marketing spending by few or spread across the players. These factors are represented graphically in Figure 1.

Insert Figure 1 here

Competitive behavior is expressed by the reactions of each firm with each marketing instrument (Horvàth, Leeflang, Wierenga and Wittink 2005, Hanssens 1980, Leeflang and Wittink 1996). At the industry level, however, this results in the use by the firms of each of the marketing instruments to some degree. It is this notion that we use to represent the first dimension of industry level competitive behavior. The second factor recognizes that firms have different competitive strategies (in part due to firm differences in resources). Therefore, this second characteristic at the industry level reflects the distribution of the marketing spending across the competitors. In addition to these two industry level characteristics of competitive behaviors, our conceptual framework shown in Figure 1 also introduces two moderating factors, the market structure reflected by many or few competitors and the level of marketing spending invested by the industry. The rationale for the various relationships among these factors is developed below and specific research hypotheses follow.

2.1 The Impact of Marketing Breadth

As pointed out above, marketing spending breadth characterizes the behavior of firms in a market by considering the extent to which firms use the spectrum of marketing instruments, i.e., the extent to which they allocate their spending across instruments versus a narrow breadth where spending is focused on only one instrument. Consequently, we define the breadth of marketing spending by an industry as the extent to which firms in the industry as a whole spread their marketing investments across the multiple instruments available. Our thesis is that the breadth of competitive reactions has mixed effects on the growth rate of the market and the final penetration of the category.

On the one hand, Gatignon, Robertson and Fein (1997) argue that a broad reaction from the incumbent is negatively related to the success of reaction. A broad reaction is unlikely to properly account for varying marketing instrument elasticities (Gatignon, Anderson and Helsen 1989). The spread of resources across marketing variables would seem to dilute the overall reaction effect and to indicate a lack of focus. Meanwhile, the use of multiple marketing instruments will lead to heterogeneity in the way that the market responds to various marketing mix elements, thus generating more awareness across different segments. In other words, a broad reaction makes the entrant's life easier while the incumbents will try to accelerate the growth of the category so as to compensate for the loss of market share. Therefore, a broad reaction tends to lead to higher growth and higher penetration of the category.

On the other hand, a broad reaction takes advantage of all the means at hand to counter the entrant. There is evidence that high levels of activity on one element can affect the responsiveness of other ones (Hanssens 1980). As the market evolves and matures, more competitors enter the market, making entry blocking less effective and less profitable. Broader spending serves to generate awareness across different consumer segments, resulting in an increase in the growth rate. Therefore, with a broad reaction, the incumbents can benefit from possible multiplier effect among the marketing mix variables. Furthermore, a broad reaction makes it more difficult for a potential competitor to generate awareness and consequently trial for its product and more difficult to differentiate itself from incumbents. Stated in another way, a broad reaction may serve as a mean of entry deterrence. This entry deterrence effect might contribute to short-term development of the market for the incumbents but leads to a lower level of penetration in the long run due to reduced competition. Ordover and Saloner (1989) find that firms use exclusive agreements to foreclose distribution channels. There is also evidence from the tobacco industry that fighter brands are used to blockade entry on retail shelves (Caves and Porter 1977).

These conflicting effects may be difficult to detect because when they are simultaneous, they may counterbalance each other. The overall effect of marketing breadth on short-term category sales is more of an equilibrium outcome. Therefore, we study the longitudinal effects of marketing breadth. In particular, we measure the breadth of marketing spending at the industry level and examine its impact on the growth rate of the category. Our thesis is that the impact of marketing spending breadth is linked to the evolution of the market. The explanation *uses* the ease or difficulty of entry which is tied to the number of competitors. However, our explanation goes beyond the effect of the number of competitors which we control for.

In the early stage of a category expansion, there are few competitors; this suggests that collusive behavior (either coordinated or tacit) is more likely (Stigler 1964). Here, broader spending at the category level is mainly to blockade the market, thus the market grows more slowly. It should be pointed out that this argument is based on the notion that when the number of firms in a category is small, it is easier for them to monitor the behavior (in terms of marketing activity) of each other than when the number of firms is large. The same rationale is used to explain competitive reactions by firms in oligopolies: when the number of competitors is small, firms tend to react to each other. Therefore, it is not the number of competitors per se that matters but the fact that there are a sufficiently small number of competitors for each of the players to monitor the marketing activities and spending of others. This leads to the first hypotheses:

H1: *When there are many competitors, broader marketing spending increases the market growth rate.*

H2: *When there are few competitors, broader marketing spending decreases the market growth rate.*

2.2 Marketing Spending Level Concentration

We introduced the notion of marketing spending concentration as reflecting the distribution of the marketing spending in an industry among the competitors. At one end of the spectrum, one competitor might dominate the market with its marketing investments; at the other extreme all firms may have similar marketing budget sizes. Notice that the spending concentration is not simply the inverse of marketing breadth. While marketing breadth measures the industry level spending across different *marketing variables* (e.g., total advertising in the industry, total sampling, sales-force, etc.), spending concentration measures the overall spending across *firms*. The former is driven by the focus of marketing activities and the latter resembles the Herfindahl index for marketing budget in the industry. A priori, it appears difficult to develop a rationale for a simple effect of this variable on market growth. Market growth is unlikely to have a simple monotonic relationship to spending concentration. In fact, it is the interaction of the marketing spending concentration and the marketing spending level of the industry that jointly determines market growth.

Intuitively, higher concentration means a few firms dominate the market and tacit collusion is possible. Generally, oligopolists try to avoid head-on competition and consequently their marketing activities should be more effective in stimulating category growth. Thus higher marketing concentration will increase the growth rate of the category. This is particularly significant at the early stage of a category, when firms will be more focused on the overall market expansion and will be less willing to fight for market share. However, this may change as the category becomes more mature and increased level of marketing spending is employed to steal market share from competitors. The relative effectiveness of marketing as a function of marketing levels is well documented both empirically and experimentally in many contexts (Eastlack and Rao 1986 and Ansolabehere and Iyengar 1995). In fact, Ansolabehere and Iyengar (1995) show that when levels of spending are high, the main motivation to spend is to cancel the efforts of the competitor. The higher the levels of spending by firms, the stronger is the cancelling out effect. Moreover, more concentrated marketing spending means that those firms are spending at higher levels. In these conditions, the cancelling out effect should be stronger. As a result, higher levels of marketing spending reduce the effect of marketing concentration on market growth. Understandably, a higher level of concentration in marketing may still help the category growth but less so when the total level of spending is high.

Thus, we postulate that at low levels of overall market spending, high degrees of concentration in marketing spending will increase the market growth rate. In contrast, a high level of total marketing spending is an indication of a highly competitive market where the cancelling out effect of marketing spending is significant. Consequently, the effect of concentration is moderated. Therefore:

H3: *Higher degree of concentration in marketing spending increases market growth rate,.*

H4: *When the total level of spending increases, the impact of a higher degree of concentration in marketing spending on market growth decreases.*

3 Data

Because the focus of our study is on growth rate, the data needed to test our model must cover all the stages of the Product Life Cycle, from the introductory stage to the maturity stage. As a result, to fully test our hypotheses, we need comprehensive sales data and data on marketing activity from the early stages of market development to maturity. The pharmaceutical industry offers features well suited to test our hypotheses because: 1) categories are clearly identified by therapeutic classes, 2) new drugs emerge throughout the category life cycle and the market is eventually filled by various competitors and 3) price are regulated and remain relatively constant over time (as a result, their impact on "changes" in growth rate is negligible). Using different market structures and behaviors across multiple countries also provide variability that allows us to test our hypotheses. We consulted with IMS Health and identified three categories that are appropriate for our analysis and for which data could be obtained: angiotensin receptor blockers (ARB), erectile dysfunction drugs (EDD), and Statins.

ARB is used for the treatment of hypertension (high blood pressure) where the patient is intolerant of ACE inhibitor therapy, diabetic nephropathy (kidney damage due to diabetes), and congestive heart failure. It was first introduced in 1995 by Merck under the trade name Cozaar and Hyzaar. Our second category is the more recently launched category of Erectile Dysfunction Drugs (EDD). The first approved EDD was introduced by Pfizer under the trade name of Caverject in 1994. While the injectables signified the start of the category, the market for EDD really began to boom with the introduction of Viagra from Pfizer in 1998. Viagra was the first of the PDE5 inhibitors, a treatment for erectile dysfunction that can be taken orally. By the end of our data (2010), three PDE5 inhibitors were on the market (Viagra, Cialis and Levitra). The third category in our data is the statins, a class of drugs used to lower cholesterol levels and these are prescribed for the treatment and prevention of cardiovascular disease. The first statin was introduced by Merck in 1987 under the trade name of Mevacor. The most popular names in this category include Lipitor and Zocor.

Our data contain the quarterly sales and marketing spending on different marketing variables (detailing, journal advertising, and direct mail advertising) from 1995 to 2010 across 7 countries (Canada, France, Germany, Italy, Spain, UK and US). When a sales representative contacts a doctor directly to promote a pharmaceutical product, it is known as detailing. The cost of detailing is jointly calculated by IMS and pharmaceutical industry experts in each country. Journal advertising includes the cost of advertisement size, position in the journal, color, insert charges and the cost of artwork in some countries. Direct mail advertising is the promotional cost of producing mailed literature, including the cost of materials, number of colors used, special folds/cuts, and the postage and packing.

4 The model

In a multilevel estimation with random intercepts, the source of variance from each level is reflected by the unconditional Interclass Correlation (ICC) i.e., the ratio of explained variance at each level divided by the total variance. The ICC coefficients for our data indicate that 3.4% of the variance is due to country and 69.9% of the variance is due to categories. The ICC statistics show that significant variance come from the drug category. This should not be surprising given the distinct nature of each drug class that we use for our analysis.[1] The fact that these drugs are so important for all countries also explains the

[1] One drug class is used to treat a chronic condition (high cholesterol levels), one drug class is used to treat high blood pressure which in many cases is an acute problem and one drug class is used to address a sexual problem.

smaller variation across countries. The goal of our model is to explain these variances at the category level and over time.

One of the two main determinants of market growth shown on the left side of Figure 1 is the variable "marketing spending breadth". Broader marketing spending means that the industry spending is more evenly distributed across the three marketing variables and narrower spending means most marketing activities are focused on one marketing variable. The variable is with a term that is associated with the Herfindahl concentration index commonly used in competitive industry analysis:

$H = \sum_{i=1}^{N} s_i^2$, where s_i is the market share of firm i and N is the number of firms.

The Herfindahl index measures the degree of market share concentration by a few firms. Our measure of marketing breadth is based on the share of spending from each *marketing variable*. Therefore, we use a version of the Herfindahl index and measure the breadth of marketing spending as the inverse of a concentration index across the three marketing variables. More specifically, marketing spending breadth is defined operationally at the market level as:

$$\text{Breadth}_t = 2 - \frac{detailing_t^2 + mail_t^2 + journal_t^2}{(detailing_t + mail_t + journal_t)^2} \tag{1}$$

Where:

Breadth_t = Marketing spending breadth at time t,
$detailing_t$ = Total amount of detailing spent by all competitors in market at time t,
$mail_t$ = Total amount of mailing spent by all competitors in market at time t,
$journal_t$ = Total amount of journal advertising spent by all competitors in market at time t,

As explained earlier in our conceptual definition, Breadth_t is a measure of how spending is distributed across different marketing variables in the market at a period *t*. When all spending is on a single marketing variable, Breadth_t=1. When the spending is evenly distributed across all three variables, Breadth_t=1.67. Thus a higher value in Breadth means the spending is more broadly allocated across different marketing mix variables. Notice that the Breadth variable is always larger than 1. This is adopted to ensure the logarithm functions produce non-negative values in our category growth model.

Our second variable of interest is the marketing concentration index across firms. This refers to whether the overall spending on the market is from a few firms or from all competing firms. We follow the definition of Herfindahl Index and use the share of marketing spending for each firm to measure the marketing concentration. Let us denote by N_t the number of firms on the market at time t. Then, marketing spending concentration is defined as:

$$\text{Mktg\_Spend\_Conc}_t = \sum_{k=1}^{ncomp_t} \frac{(total\_mktg\_spending_{kt})^2}{(\sum_{k=1}^{ncomp_t} total\_mktg\_spending_{kt})^2} \tag{2}$$

Where:

Mktg_Spend_Conc$_t$ = Marketing spending concentration at time t,
total_mktg_spending$_{kt}$ = Total marketing spending by firm k at time t,

The variable Mktg_Spend_Conc$_t$ is an inclusive measure of competitive concentration. When all marketing expenditures come from a single firm, Mktg_Spend_Conc$_t$ =*1*. When each firm spends identical amounts, the lowest possible degree of concentration in marketing expenditures, $\text{Mktg\_Spend\_Conc}_t = \frac{1}{N_t}$. Because $N_t \geq 1$, $\text{Mktg\_Spend\_Conc}_t \leq 1$. The higher the value of Mktg_Spend_Conc$_t$, the more concentrated is the marketing spending. Furthermore, since Mktg_Spend_Conc$_t$ is related to the number of firms in the market (N_t), it also measures the degree of concentration in non-marketing related terms, e.g., oligopoly or monopolistic competition (Vives 1999).

Our conceptual framework suggests that the impact of the breadth is affected by the number of competitors on the market. However, this effect is not linear as we expect a threshold. In particular, the use of marketing breadth to foreclose markets to new entrants implies a degree of coordination between the incumbents to make the barriers effective. When the number of firms exceeds a threshold, the coordination becomes difficult if not impossible (Carlton and Perloff 2000). Where the threshold should be set is an empirical question though judicial inquiries regarding non-competitive behavior suggest a threshold of around 4 firms.[2] To capture this effect, we define the dummy variable "Few": [3]

$$Few_t = \begin{cases} 1 \;\; if \;\; N_t < 4 \\ 0 \;\; if \;\; N_t \geq 4 \end{cases} \tag{3}$$

Consistent with previous research (Farley and Lehmann 1986, Shankar 1999), we use a log-linear function to describe the sales response at the market level:

$$ln(S_{tij}) = \alpha_{ij0} - \Phi_{tij} / t_{ij} + \alpha_{ij1} Ln(\text{TotalMktg}_{tij}) + \alpha_{ij2}\text{Few}_{tij} + \epsilon_{tij}, \tag{4}$$

Where:

S_{tij} = total sales of the category j in country i at time t,

t_{ij} = the time since the first launch of category j in country i,

TotalMktg$_{tij}$ = the sum of the marketing spending across firms in country i and category j, ϵ_{tij} is the error term normally distributed with mean 0 and variance σ^2, and α_{ij0}, Φ_{tij}, α_{ij1}, α_{ij2} are the parameters.

Parameter Φ_{tij} essentially captures the diffusion of the category (Kalyanaram and Urban 1992, Shankar 1999). If category sales are growing over time, then Φ_{tij} is positive. Therefore, it measures the growth rate of the category, i.e., the higher the value of Φ_{tij}, the faster sales are growing. To see this, one can examine the difference in sales at time $t+1$ and t while assuming all other things equal:

$$ln(S_{t+1}) - ln(S_t) = \frac{\Phi}{t(t+1)}. \tag{5}$$

When Φ is positive (sales grow), the higher its value, the larger the difference between S_{t+1} and S_t (see Figure 2 for an example).

[2] The ability of firms to coordinate in way to reduce competition has been studied extensively in the industrial organization literature. Moreover, in a study by Fraas and Greer (1977), the most common type of case brought to the Department of Justice alleging cartel-like behavior involved 4 firms.

[3] Alternative specifications of Few$_t$ will be discussed later.

Insert Figure 2 about here

In other words, the parameter Φ_{tij} can be used as a measure of the growth rate of the category. Our theory suggests that this growth rate is influenced by the breadth of marketing spending and the degree of competitive concentration. Simultaneously, we posit that the influence of spending breadth on growth rate is moderated by the number of competitors and the influence of spending concentration is moderated by the total level of category marketing spend. Therefore, we decompose the growth rate measure as follows:

$$\Phi_{tij} = \beta_{ij0} + \beta_{tij1}, \tag{6}$$

$$\beta_{tij1} = (\gamma_0 + \gamma_1 \text{Few}_{tij})\text{Breadth}_{tij} + (\gamma_2 + \gamma_3 Ln(\text{TotalMktg}_{tij}))\text{Mktg\_Spend\_Conc}_{tij}. \tag{7}$$

When there are only a few competitors on the market, Few_{tij}=1, the impact of marketing breadth is reflected by $\gamma_0 + \gamma_1$. When there are many competitors, Few_{tij}=0, the impact is measured by γ_0. Consequently, our hypotheses H_1 and H_2 imply that the estimation should show that $\gamma_0 > 0$ and $\gamma_1 < 0$ respectively.

Similarly, the impact of marketing spending concentration when the logarithm of TotalMkktg_{tij} is 0 is reflected by γ_2; this effect is moderated by total marketing spending within the category, which is reflected through γ_3. Consequently, our hypotheses H_3 and H_4 imply that $\gamma_2 > 0$ and $\gamma_3 < 0$. The parameters corresponding to the hypotheses are shown in Figure 1 to facilitate interpretation of the parameters in relation to the hypotheses we are testing. The nature of our data is clearly hierarchical with units defined at time t within category and within country. Accordingly, we use a hierarchical linear model specification to capture the potential heterogeneity of coefficients across countries and categories. More specifically, the sales response function in Equation (4) is the first level. The second and the third level are described as follows:

Second Level (within a category and across countries):

$\alpha_{ij0} = z_{j0} + \nu_{ij0}$, where $\nu_{ij0} \sim N(0, \tau_{i0})$

$\alpha_{ij1} = z_{j1} + \nu_{ij1}$, where $\nu_{ij1} \sim N(0, \tau_{i1})$

$\alpha_{ij2} = z_{j2} + \nu_{ij2}$, where $\nu_{ij2} \sim N(0, \tau_{i2})$

$\beta_{ij0} = z_{j3} + \nu_{ij3}$, where $\nu_{ij3} \sim N(0, \tau_{i3})$

Third Level (within a category and within a country):

$z_{j0} = \mu_0 + \omega_{j0}$, where $\omega_{j0} \sim N(0, \nu_0)$

$z_{j1} = \mu_1 + \omega_{j1}$, where $\omega_{j1} \sim N(0, \nu_1)$

$z_{j2} = \mu_2 + \omega_{j2}$, where $\omega_{j2} \sim N(0, \nu_2)$

$z_{j3} = \mu_3 + \omega_{j3}$, where $\omega_{j3} \sim N(0, \nu_3)$

Our hypotheses can be assessed because of the variability in growth rates and competitive environments provided by the multilevel observations. Observations across several countries reflect competitive structure heterogeneity. Although the product categories do exhibit overlap over the product life cycle, there are clear differences in their coverage. The statin data start in 1995 when there are already more than 8 brands in the statin market. As a result, the first observation period for the statin category is not during the introduction period. Similarly, the EDD category had not reached full maturity in 2010 (the last observations in our data set are from 2010). In fact, in 2010, there were only 4 brands approved by FDA in the EDD category.[4] The overall heterogeneity of growth across the product categories allows us to estimate parameters across different stages of the Product Life Cycle. Nevertheless, we examine the robustness of our findings by splitting the data and examining the parameters for categories individually. In particular, we contrast the results of the ARB category where we have complete data for each country to the other product categories that only cover part of the product life cycle.

Two issues emerge when estimating a model of market growth at the industry level. The first one is autocorrelation. Aside from 3 cases (out of the 21 category-markets we examine), the Durbin-Watson statistics indicate that autocorrelation is not significant (Table 1).

Insert Table 1 about here

[4] There are other non-FDA approved brands prescribed for ED but their sales are minimal and there is little marketing spending for these brands. We retained those brands in the analysis but their contribution to the category is through their impact on the number of competitors.

The second issue in estimation is the possible endogeneity between marketing spending and market growth. Our approach to control for this possible endogeneity is to implement a two-stage estimation. In a first stage, we use only exogenous variables as instruments to predict the potentially endogenous variables (i.e., marketing breadth and marketing spending concentration). The variables include industry structure variables (e.g., number of competitors) and lagged variables. Two-stage least squares is used due to the simultaneity of "marketing breadth" and "marketing spending concentration".

$$\begin{cases} Breadth_t = \theta_0 + \theta_1 \ln(S_{t-1}) + \theta_2 \ln(ncomp_t) + \theta_3 Breadth_{t-1} + \theta_4 Mktg\_Spend\_Conc_t + \delta_t, \\ Mktg\_Spend\_Conc_t = \lambda_0 + \lambda_1 \ln(S_{t-1}) + \lambda_2 \ln(ncomp_t) + \lambda_3 Mktg\_Spend\_Conc_t + \lambda_4 Breadth_{t-1} + \varsigma_t \end{cases}$$

In a second stage, we then use the *predicted* "Breadth" and "Mktg_Spend_Conc" to estimate the hierarchical linear model. The estimation of the hierarchical model is performed using the EM process in Stata. In the Appendix, we also provide the estimates using the original (i.e., NOT the predicted values) "Breadth" and "Mktg_Spend_Conc" (Table 3). The results are qualitatively similar with minor variations in significance levels.

5 Estimation results

Table 2 provides the estimates of the parameters. The parameter estimates of the analysis incorporating the three categories are shown in the right columns of Table 2. In addition, we report the results for the analysis of individual product categories.

Insert Table 2 about here

The first observation from the results is that the estimated coefficients of the control variables (i.e., "total marketing spending" and "Few") are consistent with our expectations, even though they are not the focus of this study. In particular, higher levels of marketing spending increase category sales ($\alpha_1 > 0$). Also, more competitors tend to increase overall category sales ($\alpha_2 < 0$, recall that Few=0 if there are more than 4 competitors).

Our main objective is to examine the impact of marketing breadth and competitive concentration through the following equation which decomposes the growth rate consistent with equation 7:

$$\Phi_t = \beta_0 + (\gamma_0 + \gamma_1 \text{Few}_{tij})\text{Breadth}_{tij} + (\gamma_2 + \gamma_3 \ln(\text{TotalMktg}_{tij}))Mktg\_Spend\_Conc_{tij}. \quad (8)$$

In the above equation, Φ_t is the overall category growth rate, and the parameter β_0 essentially measures base level growth of the category. In all three categories, the estimates of β_0 are significant and positive. The base level growth is consistent with our model specification, i.e., a positive β_0 means higher growth in an exponential category growth model.

The growth rate is also affected by the industry level marketing activities. We first report the pooled estimates across categories that are the basis for the overall tests of our hypotheses. Then, we provide further insights by discussing the results for each category when we can identify effects under specific competitive structures.

Replacing the coefficients in Equation (6) with the pooled estimates in Table 2, we have:

$$\beta_1 = (16.03 - 15.90\text{Few})\text{Breadth} + (6.25\text{-}0.67\text{Ln}(\text{TotalMktg}_t))\text{Mktg\_Spend\_Conc}_t \quad (9)$$

The first item on the right hand side of equation 9 supports Hypothesis 2 and also supports Hypothesis 1 although to a lesser extent. In particular, when there are many competing firms on the market (Few=0), broader marketing spending increases market growth ($\gamma_0 = 16.03$). This confirms Hypothesis 2. However, when there are only a few competitors (Few=1), the impact of broader spending is strongly moderated ($\gamma_1 = -15.90$). The overall effect of marketing breadth is not helping the category growth ($\gamma_0 + \gamma_1 = 0.13$, insignificant).

The second item in Equation (9) is related to Hypotheses 3 and 4. The estimated coefficient for "marketing spending concentration" is positive ($\gamma_2 = 6.25 > 0$), meaning that higher concentration increases the category growth rate. This confirms Hypothesis 3. Further more, we also found that $\gamma_3 = -0.67 < 0$. This indicates that higher level of total marketing spending reduces the effect of marketing concentration, which confirms Hypothesis 4.

The estimates from the pooled data support most of our hypotheses (Hypothesis 1 is only weakly supported). To understand the inherent driving forces of market growth, we now turn to each category and discuss the results. We shall start with the ARB category. The ARB drug is particularly suitable for the purpose of our analysis: the first product was launched in 1995, coinciding with the start of our dataset. And by 2010, there are more than 8 competing brands in each category in most countries. This means, the category is well aligned with our data requirement: a category from its beginning to maturity.

The estimates strongly support both Hypotheses 1 and 2. In particular, when there are only a few competitors, broader marketing mix decreases market growth rate (Few=1, $\gamma_0 + \gamma_1 = 15.77 - 21.53 < 0$). However, when there are many competitors (Few=0), broader marketing spending tends to increase market growth ($\gamma_0 = 15.77$).

The results from the ARB category also confirm our Hypotheses 3 and 4 ($\gamma_2 = 11.21$ and $\gamma_3 = -1.10$). It is interesting to note that in the ARB data, the value of $\ln(\text{TotalMktg})$ ranges from 6.14 to 11.52. This suggests that when the total marketing spending is high (i.e., $\ln(\text{TotalMktg})$ approaching 11.52), higher marketing concentration may even decrease the category growth (11.21-1.1x11.52=-1.46<0).

The estimates from the EDD data exhibit qualitatively similar results. Here $\gamma_0 = 14.29$ and $\gamma_1 = -10.63$. This confirms Hypothesis 1 that broader marketing spending increases category growth when there are many competitors. However, Hypothesis 2 is not fully supported even though we do find that fewer competitors do decrease the impact of marketing breadth ($\gamma_1 < 0$). Notice that here $\gamma_0 + \gamma_1 = 3.66 > 0$. While this implies that marketing breadth increases growth rate even when there are only a few competitor (Few=1), it may be a function of the current competitive situation in the EDD category. Until 2010, three major PDE5 inhibitor brands (Viagra, Cialis and Levitra) have dominated the marketing spending in this category. Our hypothesis builds on the conjecture that as a category becomes mature; more firms will enter and engage in competitive marketing activities. As of 2010, this is not the case with EDD as perhaps the category has not yet reached maturity. The big three PDE5 inhibitor brands behave in an oligopolistic fashion and carefully differentiate themselves. Consequently, a change in the dummy variable “Few” is not associated with enough changes in the nature and the impact of marketing breadth. To further check our intuition, we run the model under two alternative specifications: 1) with only the three PDE5 inhibitor brands and 2) with a lower threshold for “Few” (Few=1 if N<2). The estimates are provided in Table 4 and they confirm our conjecture. When the threshold for the dummy variable “Few” changes to 2 then $\gamma_0 + \gamma_1 < 0$. When only PDE5 inhibitors brands are used (maximal number of competitors is 3, thus “Few=1” always), the estimate of γ_0 is insignificant. This suggests that broader marketing spending does not accelerate category growth at the stage of the life cycle when there are few competitors.

The estimates of γ_2 and γ_3 are not significant when the threshold of 4 for Few is used (see the EDD column in Table 2 for 2-level HLM). However, they are significant in Table 4 under the alternative specification of a threshold of 2 competitors or when only the top three competitors are considered. This reflects the unique competitive scenario in this category where three major brands dominate the marketing spending. Nevertheless, the signs of γ_2 and γ_3 are consistent with the estimates from the ARB markets and thereby confirm Hypotheses 3 and 4. Moreover, in EDD markets, the value of $\ln(\text{TotalMktg})$ ranges from 3.59 to 10.63. This again points to the idea that higher marketing concentration may decrease the category growth (8.95-1.42x10.63=-6.14<0).

The estimates from the statins data exhibit similar results. Because by 1995, the earliest date of our data, there were already more than 8 statin brands in each country, we always have “Few=0” for the statin markets. Therefore, the estimate of γ_0 measures the effect of breadth when there are many competitors. This is insignificant, which is consistent with Hypothesis 2. Meanwhile, we do find that our hypotheses with respect to the effect of marketing concentration are confirmed by the statins data. Here $\gamma_2 = 107.97$ and $\gamma_3 = -12.53$. The value of $\ln(\text{TotalMktg})$ in statins markets ranges from 6.28 to 11.72. This again confirms that higher marketing concentration decreases the category growth (107.97-12.53x11.72=-38.89<0).

In sum, our model produces similar results across different categories although with varying degree of significance: this is to be expected as splitting the observations reduces the variance in the data and leads to less significant results.

In the above estimation, we have used the threshold of 4 competitors to define the dummy variable "Few". In this section, we examine the robustness of such specification by varying the threshold. To maintain the internal consistency, we focus on the data from the ARB category. This is because ARB is the one category where the number of competitors grows from one to more than nine (or even up to 30 in certain countries). Table 5 summarizes the estimates under different specifications of "Few".

Insert Table 5 about here

It appears that the results are most significant when "Few" is defined at the threshold of three or four competitors, with a threshold of three competitors being slightly better than four. Even though we argue that the impact of marketing breadth is not a continuous function of the number of competitors, number of competitors is often used as an explanatory variable in industrial organization empirical work. We therefore estimated a model where the threshold explanation was replaced with the number of competitors. The result pertaining to "number of competitors" is insignificant, even though the signs of the estimated coefficients are as expected. These results highlight the justification of specifying a threshold competitive level consistent with economic theory defining collusive feasibility.

6. Discussion

The primary goal of this paper has been to offer insight into factors that explain the growth rates in categories as they evolve over time from the introductory stage, through the growth stage and finally into maturity. Our focus is factors that characterize the nature of competitive interactions within a category. This builds on the idea that competitive dynamics is fundamentally linked to market evolution: nevertheless, this link has been understudied to date by academics (Soberman and Gatignon 2005). Obviously the evolution of a category in any given country is idiosyncratic: factors that impact category growth are different in each case due to differences in the sequence or space between launches (across countries), differences in the decisions that managers make (responsible for products in different countries), differences in the regulatory environment for different categories and differences across countries in terms of regulation as well. As a result, to uncover and identify relationships that are general across categories (and even countries) is difficult. Yet that is what we aim to do in this paper. There are four key strategies that we employ to approach this task as efficiently as possible.

First, we have chosen to conduct this study in pharmaceutical categories for which all sales are governed by prescriptions written by physicians. This provides us with a number of advantages which specifically address a number of the challenges highlighted above: growth in many categories is highly affected by the pricing policies of competing firms and the price and marketing actions of firm in other categories which are either substitutes or complements for the category in question. An advantage of the pharmaceutical categories we study is that prices are regulated and fixed for long periods (which in general, limits the importance and role of pricing as a competitive marketing tool). Second, the categories we study are for the most part, the only solution (or treatment) for a specific class of therapeutic problem. As a result, the impact that the pricing and marketing actions of other categories on growth in the categories we study is limited if not negligible. A further advantage of these categories is that comprehensive data has been obtained with standardized definitions on all the major marketing levers that firms use to promote the sale (and use of) these products. As a result, reduced unexplained variance is a key advantage that aids to uncover the relationships we want to analyze.

Second, there are significant differences across countries in the rate and pattern of diffusion that products follow (Gatignon, Eliashberg and Robertson 1989). However, the purpose of this paper is to identify relationships that are universal and hence common across countries. Hence, it is important to assess the relationship of competitive dynamic factors to market growth across countries to confirm the generality of the relationships. A key advantage of the categories we have chosen is that they have been introduced across a significant number of key countries within years if not months of each other. Moreover, the data is available. Admittedly, these categories generally appear first in the United States but approvals in other countries (in our sample) follow shortly thereafter. Importantly, the use of these products is essentially identical across countries and this also facilitates the assessment of the relationships that interest us.

Third, the categories we have chosen also allow us to study the complete evolution of markets from the introductory stage up to relatively advanced levels of maturity. In general, the categories in question take anywhere from 5-10 years before reaching maturity. A key advantage of the categories we study is that all stages of the product life cycle (except the decline stage) are covered by our data. The lack of data from the decline stage is not of major concern as the hypotheses that interest us focus on how the relationships between competitive dynamic factor and market growth change from *the early stages of category introduction over time as the category progresses towards maturity*. As a result, our findings are not derived from "trends" but from the measured relationship of factors such as the Breadth of Marketing Spending on Market Growth at specific points along the product life cycle.

Finally, a critical challenge with an analysis such as this is the endogeneity of independent variables such as the Breadth of Marketing Spending and Marketing Concentration. For example, it is well known that companies often have policies that fix certain elements of marketing spending as a function of sales (hence, the perennial interest in advertising to sales ratios). Despite the argument that advertising levels might be "fixed" as a function of forecasted sales, the endogeneity problem remains. Forecasted numbers are invariably estimated utilizing historical trends and past sales. Thus, a key challenge when analyzing such relationships is to account for such endogeneity: basically once endogeneity is accounted for, the objective is to assess whether the postulated relationship can be identified. Because of the nature of our data set (which is longitudinal and contains a number of exogenous variables), we are able to correct for this problem with a 2-stage estimation wherein predicted estimates of critical independent variables subject to endogeneity (generated with instrumental variables), are used to assess the relationships. With this procedure, we are able to confirm that the results are not qualitatively affected by endogeneity.

In sum, the four strategies listed above are instrumental in allowing us to uncover relationships between competitive interactions and the evolution of markets. In the past, a number of papers have postulated changes in these relationships. However, ours is the first paper to confirm these changes empirically.

7. Conclusion

Our objective was to build a model that would allow us to better understand how competitive marketing activities, namely the breadth of marketing spending across different marketing mix variables and the degree of concentration in marketing spending (across participating firms), impact category growth over time. Our analysis shows that when there are few competing firms in the market (as is the case early in the life of a category), broader spending reduces market growth because of how broad marketing spending can blockade entry. This obtains because, on average, tacit (or explicit) collusion allows firms to make entry either unattractive or difficult for potential entrants. However, consistent with industrial organization theory (Fraas and Greer 1977), this becomes less feasible as the number of competitors increases. When there are many competitors, broader marketing spending performs the more expected role of activating increased numbers of customers and expanding the market: this is of course reflected in higher levels of market growth.

We further show that with the analysis that category growth is closely related to (and influenced by) the degree of competitive concentration. To be specific, when marketing activities are dominated by a few firms, head-on competition is avoided and this leads to efficient marketing spending which fuels category growth. However, as the total level of spending increases, the marginal effectiveness of each marketing variable decreases and coordinated marketing activities by competing firms are less likely. This leads to more cancelling-out, especially when marketing spending is concentrated. Accordingly, our empirical analysis shows that high degrees of marketing concentration do not increase category growth when the total level of spending in the industry is high. We should note that this situation is primarily observed as categories start to mature.

To conclude, we see our paper a first step in trying to elucidate the complex relationship between the competitive dynamics of a category and the rate at which a category expands. The analysis confirms a number of fundamental insights about markets that are based on a combination of ideas derived from industrial organization theory and also from diffusion theory. We see this as important first step. Not only are there more dimensions that link competitive dynamics to market evolution (in fact, our analysis abstracts away from pricing issues which are the fundamental drivers of market evolution in many categories). In addition, we believe there are a number of paths through which category growth itself affects how firms make decisions and how firms react to initiatives taken by competitors. There are issues we plan to investigate in the future.

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Figure 1 Conceptual Framework

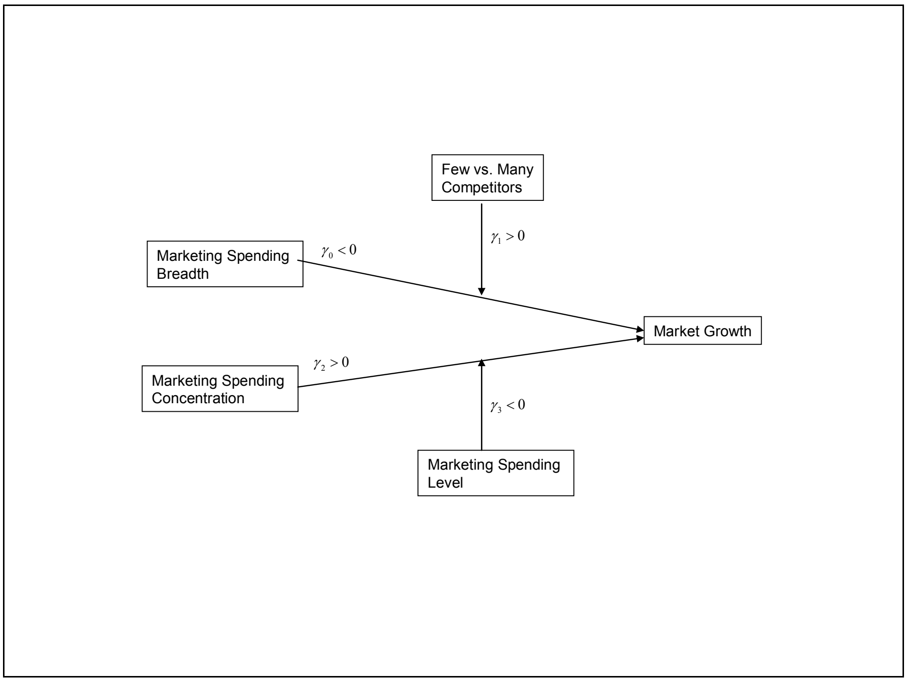

Figure 2 Examples of Market Growth Rates as a Function of Parameter Φ

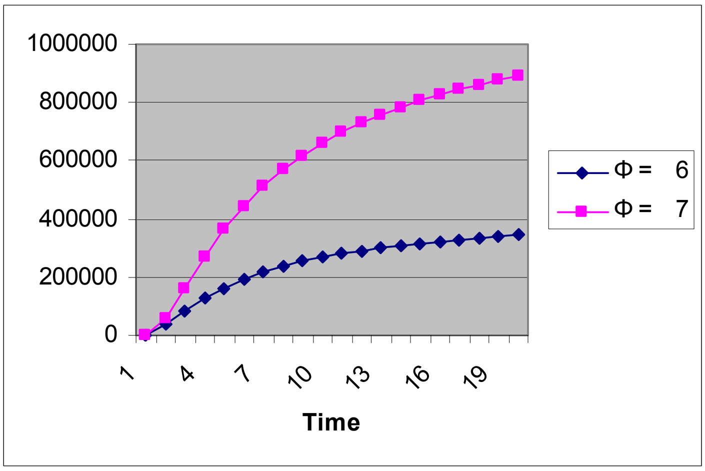

Table 1: Durbin_Watson tests

Durbin-Watson statistics

	Category		
country	ARB	EDD	Statin
Canada	DW(8,34)=2.595436 **	DW(10,34)= 2.272104 **	DW(8,34)= 2.75416 **
France	DW(8,34)=1.166898 ++	DW(8,40)= 1.815041 **	DW(8,40)= .7263299??
Germany	DW(10,57)= .8238485 ??	DW(10,50)= .9732074 ++	DW(8,60)= 1.177958 ++
Italy	DW(8,40)= 1.145122 ++	DW(10,40)= 1.912316++	DW(8,40)= .6192503 ++
Spain	DW(8,35)= 1.982243 **	DW(9,35)= 1.485664++	DW(8,35)= 1.635844 ++
UK	DW(10,59)= 1.40831 ++	DW(10,60)= 1.45021 ++	DW(10,60)= 1.107145 ++
US	DW(10,51)= 1.977092 **	DW(10,50)= 1.460523 ++	DW(8,50)= .8766154 ??

**:	>dU	reject AR1
++:	(dL, dU)	Inconclusive
??:	<dL	cannot reject AR1

all at 1% significance interval. 5% intervals will be similar

Table 2: Estimates of the Parameters for the Model of Equations 4, 6 and 7

Parameters	Individual categories (2 level HLM)						all categories	
	ARB		EDD		Statins		3 level HLM	
	estimate	std. err.	estimate	std. err.	estimate	std. err.	estimate	std. err.
α_0	12.68***	0.341	10.61***	0.274	12.55***	0.781	11.63***	0.363
α_1	0.06	0.036	0.10***	0.026	0.13**	0.066	0.119***	0.033
α_2	-2.85***	0.392	-1.13***	0.360	N/A	N/A	-1.69***	0.305
β_0	21.18***	4.676	17.89**	7.921	84.23***	11.766	27.84***	5.835
γ_0	15.77***	1.114	14.29***	1.484	-4.75	5.103	16.03***	0.833
γ_1	-21.53***	0.630	-10.63***	0.929	N/A	N/A	-15.90***	0.568
γ_2	11.21***	2.305	1.02	2.782	107.97***	41.037	6.25***	1.838
γ_3	-1.10***	0.306	-0.25	0.416	-12.53***	4.873	-0.67***	0.239

***: significant at 0.01
** : significant at 0.05
* : significant at 0.10

Table 3: Estimates using original variables

Parameters	Individual categories (2 level HLM)						all categories	
	ARB		EDD		Statins		3 level HLM	
	estimate	std. err.	estimate	std. err.	estimate	std. err.	estimate	std. err.
α_0	12.21***	0.400	10.97***	0.258	12.35***	0.828	11.74***	0.315
α_1	0.10***	0.031	0.0.07**	0.031	0.14**	0.072	0.11***	0.030
α_2	-2.77***	0.384	-1.19***	0.302	N/A	N/A	-1.59***	0.280
β_0	22.56***	4.450	38.32***	7.48	72.55***	12.026	39.22***	5.549
γ_0	13.63***	1.403	4.23**	1.734	3.74	4.795	9.98***	0.949
γ_1	-19.55***	0.804	-12.50***	0.839	N/A	N/A	-14.73***	0.525
γ_2	-0.60	3.480	8.41***	2.367	113.51**	49.410	6.36***	1.815
γ_3	-0.03	0.458	-2.19***	0.337	-14.61**	5.957	-1.81***	0.237

Table 4: Estimation of EDD data under alternative specifications

Parameters	Few=1 if ncomp$\leq$2		With only PDE5 inhibitors (Few=1 always)	
	estimate	std. err.	estimate	std. err.
α_0	10.66***	0.427	10.94***	0.340
α_1	0.08*	0.047	-0.01	0.047
α_2	-2.22***	0.547	N/A	N/A
β_0	24.28***	7.752	7.03**	3.177
γ_0	8.68***	1.397	1.36	0.963
γ_1	-10.01***	0.805	N/A	N/A
γ_2	8.95***	3.066	19.06***	4.708
γ_3	-1.42***	0.405	-2.00***	0.567

***: significant at 0.01
** : significant at 0.05
* : significant at 0.10

Table 5: Change the specification of the variable "Few"

	Few=1 if											
	ncomp ≤ 1		ncomp ≤ 2 #		ncomp ≤ 3		ncomp ≤ 4		ncomp ≤ 5		ncomp ≤ 6	
	Coef (std. err)	P>|z|	Coef (std. err)	P>|z|	Coef (std. err)	P>|z|	Coef (std. err)	P>|z|	Coef (std. err)	P>|z|	Coef (std. err)	P>|z|
α_0	13.00(.456)	0.000	13.45(0.426)	0.000	12.68(.341)	0.000	12.81(.386)	0.000	12.13(.457)	0.000	12.05(.590)	0.000
α_1	.02(.032)	0.440	-0.01(.028)	0.664	0.06(.036)	0.110	0.05(.030)	0.106	0.11(.033)	0.001	0.12(.047)	0.008
α_2	-5.35(.847)	0.000	-3.51(.119)	0.000	-2.85(.392)	0.000	-2.80(.340)	0.000	-2.14(.284)	0.000	-2.09(.296)	0.000
β_0	9.01(5.277)	0.088	21.66(5.096)	0.000	21.18(4.676)	0.000	20.76(4.655)	0.000	17.62(4.713)	0.000	14.54(4.675)	0.002
γ_0	26.82(1.489)	0.000	16.98(1.137)	0.000	15.77(1.114)	0.000	16.70(1.081)	0.000	17.35(1.387)	0.000	20.84(1.448)	0.000
γ_1	-19.05(0.672)	0.000	-20.51(0.619)	0.000	-21.53(0.630)	0.000	-21.31(.647)	0.000	-19.26(.864)	0.000	-20.29(1.071)	0.000
γ_2	15.17(3.069)	0.000	11.61(2.249)	0.000	11.21(2.305)	0.000	10.28(2.273)	0.000	5.51(2.725)	0.043	0.52(2.843)	0.856
γ_3	-3.76(0.407)	0.000	-1.30(.294)	0.000	-1.10(.306)	0.000	-0.99(.303)	0.001	-0.23(.362)	0.525	0.36(.372)	0.337

#Stata does not generate a standard error for the random effects.

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