The Roles of Marketing Breadth and Competitive Spread on Product Life Cycle

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Abstract

Understanding the patterns of demand evolution for a new innovation is critical for firms to effectively manage capacity planning, market and service operations, and research and development. The objective of this paper is to analyze how marketing at the industry level affects the evolution of primary demand in different stages of the product life cycle. We empirically analyze the growth and different types of marketing spending for product categories in the pharmaceutical industry across 7 countries. Our literature review leads to the identification of two constructs that characterize the pattern of competitive marketing spending over time: marketing breadth and competitive spread. The first construct reflects the spread of spending across *different marketing instruments* at the industry level, and the second construct reflects the spread of spending across *different firms.* Even though both construct measures a certain kind of spending spread, we find that they have qualitatively different (opposite) impact on market growth. An econometric model making use of the hierarchical nature of time observations within countries is estimated for each category. First, we find that high degrees of spending breadth impede market growth when the number of competitors is small (the category is young) but accelerate market growth when the number of competitors is higher (the category is maturing). Second, we find that high levels of competitive spread decrease category growth when spending levels are relatively low. However, as spending levels increase, the negative effect of competitive spread on demand growth all but evaporates.

Key Words: marketing breadth, competitive spread, diffusion, product life cycle, pharmaceutical industry.

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1. Introduction

It is widely accepted that the evolution of demand in a new product category is a key input for how firms manage capacity decisions, product development, manufacturing processes, and channel coordination (Balakrishnan and Pathak 2014, Carrillo 2005, Gutierrez and He 2011, Mendelson and Pillai 1999, Souza et. al. 2004). Understanding the factors that drive product life cycle is a key interest amongst scholars in production management and marketing. Apart from manufacturing capacity (Balakrishnan and Pathak 2014), product attributes and costs (Schmidt and Druehl 2005), marketing investment plays an important and positive role in the growth and evolution of markets (Schultz and Wittink 1976). Arguments to support this role have been advanced and a number of studies show that marketing spending has a positive effect on the overall growth of a category (Henssens 1980, Wilkie and Moore 1999). These general findings are important yet the complex path of how marketing influences market growth is under-researched and poorly understood. One explanation for the lack of research on this topic is that there is the confounding effect of spontaneous competition which includes price rivalry, competitive advertising and shelf space battles. Indeed, marketing competition leads to changes in firms' market shares which may no effect on category growth. Competitive dynamics and market growth are key elements to develop effective business and marketing strategies yet the links between the two areas have not been clearly identified either empirically or theoretically (Lambkin and Day 1989).

Accordingly, our objective is to analyze the complex path through which marketing fuels the growth of a category and to shed light on "how" this path changes as a category moves through the stages of the product life cycle. For this purpose, we examine several important dimensions of competition at the market level: the number of competitors, overall marketing spending level, and, importantly, the patterns of marketing spending. Patterns of marketing spending have received little attention in academia, and we focus on two important constructs that represent key characteristics of spending patterns within a category: the breadth of marketing spending (across various marketing levers) and the competitive spread of spending. The first construct, the breadth of marketing spending, relates to the degree to which marketing spending is evenly spread across the various levers that the marketers can exercise. The second construct of interest is the competitive spread in spending: the degree to which spending is evenly spread across firms versus being concentrated in one or few firms.

These two characteristics are important to understand product life cycle. First, as a market grows, firms may respond to demand changes with different marketing variables. Thus, understanding the overall effect of different marketing instruments at the category level is indispensable. This includes the overall spending level and how the spending is spread across different marketing levers. Second, firms may also respond to competition differently (e.g., head-to-head or differentiation). Therefore, at the category level, a thorough examination of competitive responses needs to consider two elements: the spending breadth across marketing variables, and the competitive spending spread (across firms). Third, a firm's spending decisions should be based on its own incentives. At the industry level, the long-term effect of firm-level decisions is unclear. For example, a head-to-head response may lead to focused spending on specific marketing instruments. If this impedes category growth at an early stage, then such a response might adversely affect firms over the long run. Understanding the impact of aggregate marketing on the product life cycle is highly important to production and operation managers. Unlike marketing managers who are in charge of marketing activities within individual firms, operation managers are more concerned about the overall impact of marketing and how fast the volume of business changes over time. To be specific, they need to carefully monitor the growth and overall demand change and make various manufacturing and inventory decisions based on forecasts of primary demand within a category. Therefore, understanding the overall effect of marketing on product life cycle helps the operations department to optimize its decisions related to production and supply chain management, as well as better communication and coordination with marketing and sales function.

We build a model in which the spread of spending (across marketing variables, i.e., salesforce, sampling, professional journal advertising and direct-to-consumer-advertising)" and "competitive spread (across firms)" moderate the relationship between overall marketing spending and category growth.

A first key finding is that a high degree of spread of marketing spending reduces category growth when there are few competitors in the market. It appears that spread acts as either a deterrent to new competitors entering the market or slows the growth of new entrants in the category. However, marketing spread can accelerate market growth when there are many competitors in the market. A second key finding is that when spending levels are relatively low, low levels of competitive spread lead to higher category growth. In contrast, when spending

levels are relatively high, high levels of competitive spread reduce category growth. This provides empirical evidence for the cancelling out of marketing efforts as categories mature (spending is high). In other words, when multiple firms engage in high levels of marketing spending, their efforts are directed towards gaining sales at the expense of competitors versus trying to expand the market.

2. Market of Interest

To empirically analyze the long-term impact of competitive market spending, one needs data for each brand from the beginning of a category to its maturity stage. That is, we need comprehensive sales data and data on marketing activity at different stages of market development. The pharmaceutical industry offers features well suited for this research because: 1) categories are clearly identified by therapeutic class (the need that the product serves), 2) new drugs emerge throughout the category life cycle and the market is eventually filled by a number of competitors and 3) prices are regulated and remain relatively stable over time (this limits the role of price as a competitive tool and allows us to focus on the competitive interactions across other marketing instruments as drivers of category growth). Another important feature of pharmaceuticals is that the purchase and consumption purpose are scientifically defined and invariant across cultures. This provides a relatively clean context to analyze category growth across countries.

3. Related Research

Early research shows that marketing contributes to growth at the aggregate market level. Pricing competition attracts consumers to the market through lower prices. Advertising provides more information about the product and category, thus generates awareness and knowledge among consumers, resulting in more consumption. Carefully planned distribution optimizes market coverage and facilitates transactions. While these marketing activities certainly contribute to firms' sales how they affect overall market growth at the aggregate level, remains unclear. Bhardwaj et al. (2005) argue that marketing activities affect overall market growth as well as pure growth in the economy. They propose several drivers of growth from a knowledge generation point of view. Empirically, several papers investigate the impact of marketing on primary demand (Hanssens 1980). Although these papers analyze the total effect of marketing on the category, they do not examine the effect of competitive dynamics on category growth.

Another key area of investigation is how competitive entry and exit affect category sales and diffusion. The number of competing firms is found to affect category demand through its influence on product development, promotion, and pricing (Horsky and Simon 1983, Parker and Gatignon 1994). For example, Kim, Bridges and Srivastava (1999) include the number of competitors as a source of variation in the parameters of a diffusion model over time. There is also work that examines how product benefits and consumer preferences affect rates of diffusion (Horsky 1990, Cestre and Darmon 1998). These studies show that improvements in product attributes lead to faster diffusion. Our interest is different. We wish to learn about how the pattern of marketing spending in a category affects market growth.

The evolution of product category sales has been analyzed with and without total category marketing effort as an explanatory variable (Bass 1969, Van den Bulte and Lilien 2001). These studies do not account for the detailed manner in which category activity is distributed across the marketing levers. Detailed analyses (at the firm level) have generally focused on better understanding the magnitude and nature of firm reactions (Horváth et al. 2005, Bowman and Gatignon 2000). However, these approaches do not account for the manner in which various competitors use their marketing instruments. One reason these studies do not account for the pattern of reactions is the lack of data. To understand the long-term impact of competitive market spending, data for each brand from the beginning of a category to its maturity stage is needed. Another reason is possible endogeneity between marketing spending and the maturity of a category (Bronnenberg et al. 2000). Our approach to study this question is to build a model at the category level, where the breadth of marketing spending and the degree of competitive concentration moderate the relationship between total marketing spending and category growth.

Despite "mixed" evidence for the overall effect of marketing actions on category growth, it is clear that any model used to analyze the link between competitive interactions and category evolution should include these actions directly as explanatory variables. This will be our approach but we also attempt to understand how the detailed character of marketing expenditures in terms of its spread across marketing levers and across firms affects category growth. These detailed characteristics have not been analyzed in previous studies of how pharmaceutical categories evolve over time.

In the next section, we explain the constructs of interest and their measures and provide our rationale as to how these measures should affect category growth.

4. The Measures of Interest

Competitive behavior is often studied by examining the reactions of each firm across similar or different marketing instruments (Horváth, Leeflang, Wierenga and Wittink 2005, Bowman and Gatignon 2000, Hanssens 1980). At the industry level, we tend to observe all firms making use of each marketing instrument to some degree. It is the degree to which firms make broad use of marketing instruments in their marketing efforts that we use as a first dimension of industry level competitive behavior. The second factor, competitive spread, recognizes that firms employ different levels of combined marketing effort. These differences may be the result of firms having chosen different strategies but it also is the natural outcome in an industry where firms have different levels of resources. Therefore, the second dimension of industry level competition reflects the distribution of the marketing spending across firms. 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 total 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.

4.1 The Breadth of Spending across the Marketing Levers

Marketing spending breadth characterizes the behavior of firms 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 industry spending is focused on a single 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 spending across the marketing instruments that pertain to the industry in question. Broad marketing spending means that the industry spending is evenly distributed across the marketing levers and narrower spending means marketing spending is focused on s subset of the levers. Our measure of marketing breadth is based on the share of spending for each *marketing lever*. Therefore, we use a version of the Herfindahl index and measure the breadth of marketing spending as the inverse of a concentration index for category spending on each marketing lever.[1] To be specific, for a category, marketing

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[1] The Herfindahl concentration index is commonly used in competitive industry analysis and it measures the degree of market share concentration within an industry (Carlton and Perloff 2000).

spending breadth is measured by the variable defined as:

$$\text{Mktg\_Breadth}_t = 1 - \frac{x_{1t}^2 + x_{2t}^2 + \cdots}{(x_{1t} + x_{2t} + \cdots)^2} \tag{1}$$

Where:

Mktg_Breadth$_t$= Marketing spending breadth at time t,
x_{1t}= Total amount of spending on marketing lever 1 (e.g., detailing) at time t,
x_{2t}= Total amount of spending on marketing lever 2 (e.g., journal advertising) at time t,
etc…

This definition reflects how spending is distributed across different marketing levers in the market at period *t*. When all spending is focused on a single marketing lever, Mktg_Breadth$_t$ =0. When the spending is evenly distributed across three variables (for example), Mktg_Breadth$_t$ =0.67. Thus, a high value in Mktg_Breadth$_t$ means the spending is more broadly allocated across the marketing mix. The literature provides limited guidance as to how the breadth of marketing spending across marketing instruments should affect category growth.

The issue of the marketing breadth is considered in studies of competitive reactions (Gatignon, Robertson and Fein 1997). Broad reactions appear to be less effective responses to competitors than targeted reactions; perhaps because broad reactions do not account for differences in marketing instrument elasticities (Gatignon, Anderson and Helsen 1989). This research however, provides little guidance as to how broad or focused marketing activity should affect category growth. The use of multiple marketing instruments should allow a greater number of potential customers to be reached or exposed to marketing activity. This should lead to higher awareness of the category across different consumer segments. If this is the case, broad spending should lead to higher growth rates for the category.

Conversely, broad spending by incumbents may be effective to make life difficult for firms that have recently entered the category (or firms that contemplate entry). Evidence from industrial organization research shows that pre-emptive behavior by established firms can be used to make successful entry costlier (Salop and Scheffman 1983). Simply put, broad-based marketing activity by incumbents may increase the difficulty for a new competitor to generate awareness and trial for a new product. Thus, broad spending may impede or slow category growth especially when growth is accelerated by new firms trying to enter the market. Entry deterrence contributes to superior profit performance for incumbents but should reduce category growth in the long run due to reduced competition. Effects such as this are documented in the

form of contracts that dominant incumbents employ with distributors and even with customers (Ordover and Saloner 1989, Aghion and Bolton 1987). Product line management can also be used to make life difficult for new entrants. When there are "space constraints", Caves and Porter (1977) show that the tobacco industry offers non-profitable "fighter brands" to occupy facings on cigarette racks and blockade entry to new firms. In the pharmaceutical industry, the analogy for "the product rack" is the time the physician has available to meet with sales representatives of pharmaceutical companies. However, substantial advertising efforts by incumbents may prevent new entrants from getting "on the radar" of physicians. Of course, as a category evolves and matures, more firms enter a category and the profit gains of making life difficult for new entrants are reduced.

These two effects of marketing breadth on category growth are difficult to detect because they are often simultaneous and counteract each other. Because of this, marketing breadth is unlikely to have a significant effect on category sales in the short term. Accordingly, our objective is to assess the long-term effect of marketing breadth as a category evolves through the stages of the lifecycle (the introductory stage, the growth stage and the maturity stage). To be specific, we measure the breadth of marketing spending in the category at each point in time and examine its impact on the growth rate. Our thesis is that the impact of marketing spending breadth on market growth depends on the evolutionary stage of the category. It relies on combining the two effects described above and thinking about how the strength of the effects should evolve as a category matures.

In the early stages of the category lifecycle, there are few competitors; here, collusive behavior (either coordinated or tacit) is more likely (Stigler 1964). This is based on the idea that when the number of firms in a category is small, it is easier for firms to coordinate their actions (Greer 1971, Sutton 1974). To assess the moderating effect that the number of competitors might have, we consider two alternative structures, one where the number of competitors is the moderator and a second, where the moderator is assumed to have a distinct cut-off beyond which firms are unable to coordinate their actions.

Both structures have empirical support. On the one hand, the number of competitors is often used in structural models to represent the degree of competitiveness in the market (Berry 1992). Indeed, recent empirical Industrial Organization models employ reduced forms where the profit function is estimated using the number of competitors as an explanatory variable (Seim 2006, Singh and Zhu 2008, Ciliberto and Tamer 2009, Datta and Sudhir 2012). On the other hand,

Carlton and Perloff (2000) suggest that when the number of firms exceeds a threshold, coordination becomes difficult if not impossible. Moreover, the ability of firms to coordinate and thereby reduce competition has been studied extensively in industrial organization; a study by Fraas and Greer (1977) finds that most cases brought to the Department of Justice alleging cartel-like behavior involve 4 or fewer firms.

The primary effect of broad marketing spending (increasing awareness) should be present throughout the lifecycle. However, this effect should be stronger when a significant fraction of potential customers is unaware of the category. The second effect of broad marketing spending (making life difficult for new entrants) should be stronger when there is a small number of firms. This leads to the first two 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.*

4.2 Competitive Spread: the Spread of Spending across Firms

As presented in the introduction, competitive spread reflects the spread of spending across firms. At one end of the spectrum, one competitor might dominate the market with its marketing investments (low competitive spread); at the other extreme, all competing firms might have similar marketing budget sizes (high competitive spread). In all likelihood, competitive spread is partly driven by the relative power of firms. This can be based on sources other than spending (e.g., a pioneering advantage, asset specificity or product effectiveness). Our analysis is concerned with assessing how variation in the distribution of marketing spending among firms affects category growth. Notice that competitive spread is unrelated to marketing breadth. Marketing breadth reflects industry level spending across different marketing levers (e.g., total advertising in the industry, total sampling, salesforce, etc.) whereas competitive spread reflects the distribution of spending across firms. The former is driven by the focus of marketing activities and the latter is based on the Herfindahl index for expenditures within an industry. First, we

define N_t as the number of firms in the market at time t. Then the measure of competitive spread we use is defined as:

$$\text{Competitive\_Spread}_t = 1 - \sum_{k=1}^{\text{ncomp}_t} \frac{(\text{total\_mktg\_spending}_{kt})^2}{(\sum_{k=1}^{\text{ncomp}_t} \text{total\_mktg\_spending}_{kt})^2}$$

(2)

Where:

$\text{Competitive\_Spread}_t$ = Marketing spending spread across firms at time t,
$\text{total\_mktg\_spending}_{kt}$ = Total marketing spending by firm k at time t,

Following the earlier discussion, when all marketing expenditures come from one firm, $\text{Competitive\_Spread}_t = 0$. This is the lowest possible value for $\text{Competitive\_Spread}_t$. Conversely, the highest possible degree of spread in marketing spending obtains when each firm spends an identical amount. This translates to $\text{Competitive\_Spread}_t = 1 - \frac{1}{N_t}$. The higher the value of $\text{Competitive\_Spread}_t$, the more evenly distributed is the marketing spending across firms. A priori, it is not clear how Competitive Spread should impact category growth. However, the relationship of $\text{Competitive\_Spread}$ to category growth is unlikely to be monotonic. $\text{Competitive\_Spread}$ could also affect category growth through an interaction with the absolute level of marketing spending level in the category. The rationale for our conjecture is as follows.

As noted earlier, industrial organization research and competition law is sensitive to the level of concentration within industries. The reason is that high concentration implies that a limited number of firms dominate the industry and when the number of firms is small, collusion is more likely and easier to orchestrate.[2] Even without colluding, oligopolists often try to limit head-on competition. A key element of limiting head-on competition may involve the creation of barriers to entry for new competitors. In any event, actions that may be optimal for the firm (or firms) may be different than actions which maximize growth of the category. We use the construct of Competitive Spread to explain the growth of the market as a whole. Obviously, the overall impact of Competitive Spread is also closely linked to the absolute level of marketing spending in the industry.

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[2] This has resulted in a significant literature related to the motivation that firms have to collude in order to limit marketing spending (Bagwell and Lee 2010).

When the category is relatively new, two factors are important. First, the aggregate level of marketing spending is relatively low.[3] Second, there are many customers who have yet to be reached by the marketing activity of firms and these (potential) customers are likely to be heterogeneous in their preferences. To the extent that competing products are differentiated in some way, the more products that a potential customer knows about, the more likely it is that she enters the market. This suggests that high levels of Competitive Spread in the early stages of the product life cycle (when aggregate marketing spending is relatively low) might accelerate category growth. Conversely, it is also possible that when Competitive Spread is high, individual firms may not be spending enough for the market to react. Firms may be spending all they can but their budgets may be less than the threshold needed to generate a reaction. This follows from the well-documented S-curve that characterizes the relationship of marketing outcomes to marketing effort (Lilien et al. 1992). Consequently, a higher value of competitive spread, together with a low level of marketing spending in the industry, may actually impede the growth of the market.

When the total level of marketing spending becomes higher, a high degree of Marketing Spread should positively affect market growth for two reasons. First, at the aggregate level, a higher level of spending means that any candidate customer is more likely to be activated. Second, a high degree of Marketing Spread means that a high proportion of the levers that firms have to reach potential customers are active: this leads to more potential consumers being reached by marketing.[4]

In a nutshell, a high level of competitive spread is likely to impede market growth when the overall spending level in the market is low (a situation that occurs early in the development of a category). However, as total marketing spending increases, the negative effect of competitive spread on category growth should diminish and might even become positive. An objective of our analysis is to assess which of these two dynamics is dominant at different stages of category growth and different levels of total spending in the industry. In summary, we believe that total marketing spending should *moderate* the relationship of competitive spread on category growth. This leads to our next set of hypotheses:

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[3] There are exceptions to this rule. A few industries are known to have high marketing expenditure in the early stage or even before the launch of a new product, e.g., movie studios spend a majority of their advertising budget before the actual launch date.

[4] An alternate interpretation is that a high level of competitive spread accelerates knowledge diffusion in the industry and hence contributes to market growth (Bhardwaj et al. 2005).

H3: *A higher degree of competitive spread in marketing spending decreases market growth rate when overall category spending is low.*

H4: *When overall category spending increases, the negative impact of high competitive spread disappears and eventually becomes positive.*

4.3 Marketing and Growth in Different Stages of a Product Category

In the previous sections, we considered the impact of marketing breadth and competitive spread on market growth. While these two variables are predicted to affect market growth differently and we also believe that their impact might change as the category moves through different stages of the category life cycle. We recognize that as a category matures, marketing spending might remain high. In this situation, the marketing activities of competitors might offset each other at the aggregate level leading to the cancelling out effect as described by the industrial organization literature.

Support for this idea is found in Osinga et al (2011) who point to the possibility of a prisoner's dilemma situation when multiple firms in a pharmaceutical category make significant investments in Direct-to-Consumer Advertising (DTCA). This work highlights the idea that when firms invest heavily to market to the same customers, the efforts of one firm are negated by the efforts of another: there is a cancelling out effect.

This dynamic should become more severe as a category matures. In a mature category, it is more difficult for a category to grow because a high fraction of potential customers has already entered the market. Accordingly, an increased proportion of marketing spending is used to steal market share from competitors. The relative effectiveness of marketing as a function of marketing levels is documented empirically and experimentally in a number of contexts (Eastlack and Rao 1986, Ansolabehere and Iyengar 1995). Ansolabehere and Iyengar (1995) show that when levels of spending are high in political campaigns, the main motivation of spending is to cancel the efforts of the opponent.

These ideas also permeate the advertising literature (Butters 1977, Grossman and Shapiro 1984). When the advertising reach of companies in the market is low, as it would be in the introductory stage of the category lifecycle, the main role of advertising is to inform or "activate"

customers. Here, a customer buys from the firm she knows about and the likelihood she knows of more than one firm is low. In contrast, when the advertising reach of companies is relatively high, as it would be in the mature stage of the category lifecycle, a firm needs advertising to inform customers about the relative benefits it provides. Here, customers have typically seen advertising from many firms and sometimes a competitor's product is a better fit with the customer's preferences. Here, information provided to the customer in the competitor's advertising cancels a significant fraction of advertising's potential benefit. It is precisely this dynamic that leads to a positive relationship between advertising levels and market growth when reach levels are low and a weak (or negligible) relationship between advertising levels and market growth when reach levels are high (Soberman 2004).

Following the above rationale, our conjecture on the long-term impact of marketing breadth and competitive spread is formulated in the hypotheses below:

H5: Both marketing breadth and competitive spread have significant impact on category growth before the market reaches full maturity.

H6: *In completely mature markets, the impact of marketing spending patterns on market growth is dominated by the strong cancelling-out effects of competitive marketing.*

5 **Data**

We utilize data from several countries on the same category. IMS Health identified three categories appropriate for the analysis and for which data were available to cover the various stages of the Product Life Cycle: angiotensin receptor blockers (ARB), erectile dysfunction drugs (EDD), and Statins. One factor that affects the use of products within a pharmaceutical category is that the number of indications increases over the category lifecycle. Not surprisingly, this in itself can be an important factor contributing to category growth. An attractive characteristic of the categories we have chosen is that their therapeutic use has exhibited little change over the time periods we examine.[5]

ARB is used for the treatment of hypertension (high blood pressure) where the patient is cannot tolerate ACE inhibitor therapy, has diabetic nephropathy (kidney damage due to diabetes),

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[5] We avoided categories where the therapeutic indication was not constant across all the competitors in the drug class. For example, we chose not to include the Chronic Obstructive Pulmonary Disease (COPD) category in the analysis. Some COPD drugs have an indication for the treatment of Asthma (a disease that is medically different but has similar symptoms).

or has 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 was legitimized 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 statins, a class of drugs used to lower cholesterol levels. 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 contains 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 the advertisement (that is a function of the size, position in the journal and color), insert charges and the cost of artwork. Direct mail advertising is the promotional cost of producing mailed literature, including the cost of materials, number of colors used, special folds/cuts, the postage and the packing. In addition, for the US, which is the only country in our dataset where DTCA spending has been significant, we obtained quarterly DTCA data from Kantar Media for the three categories we analyze.

6   The Model

The goal of our model is to explain the variance in growth rates for each category over time. Our belief is that the impact of the breadth of marketing spending on category growth is affected by the number of competitors in the market. As noted earlier, we analyze two potential structures, one that treats the number of competitors as a continuous variable and a second that models the effect as being subject to a cut-off (number of competitors) above which the collusive effect of marketing breadth is negligible. We find that the model with a discrete cut-off was superior for explaining the data. For that reason, our study is based on a model with a discrete cut-off.[6] We reflect this by defining a dummy variable "Few":

$$\text{Few}_t = \begin{cases} 1 \ if \ N_t < 4 \\ 0 \ if \ N_t \geq 4 \end{cases} \tag{3}$$

As mentioned earlier, we assume that category sales are the exponential of a linear equation that contains the explanatory variables in a structure that follows previous research (Shankar 1999). Note that index i has been added to the variables defined previously (equations 1 and 2) to reflect the multi-country nature of our analysis.

$$S_{ti} = \exp(\alpha_{i0} - \Phi_{ti}/t_i + \alpha_{i1}\ln(\text{TotalMktg}_{ti}) + \alpha_{i2}\text{Few}_{ti} + \alpha_3\text{Mktg\_Breadth}_{ti} +$$
$$\alpha_4\text{Competitive\_Spread}_{ti} + \alpha_5\text{Normalized\_Price}_{ti} + \varepsilon_{ti}) \tag{4}$$

Where:

S_{ti}= total unit sales of the category in country i at time t,
t_i= time since the first launch in country i,
TotalMktg_{ti} = the sum of the marketing spending across firms in country i at time t,
Mktg_Breadth_{ti}= the breadth of marketing spending in country i at time t,
$\text{Competitive\_Spread}_{ti}$= competitive spread across firms in country i at time t,
$\text{Normalized\_Price}_{ti}$= category price at time t *relative* to average category price over the period of analysis, i.e., $\text{Normalized\_Price}_{ti} = \frac{\text{Price}_{ti}}{\left(\sum_{t=0}^{T_i}\text{Price}_{ti}\right)/T_i}$, where T_i is the total number of observations in country i,
ε_{ti} is the error term normally distributed with mean 0 and variance σ^2, and α_{i0}, Φ_{ti}, α_{i1}, α_{i2}, α_3, α_4, α_5 are the parameters.

To estimate equation 4, we take the logarithm of both sides of the equation and use the transformed equation to estimate the sales response at the country level for each category:

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[6] Alternative specifications of Few$_t$ were investigated and are discussed in Section 5.0.

$$\ln(S_{ti}) =$$

$$\alpha_{i0} - \Phi_{ti}/t_i + \alpha_{i1} \ln(\text{TotalMktg}_{ti}) + \alpha_{i2} \text{Few}_{ti} + \alpha_3 \text{Mktg\_Breadth}_{ti} +$$

$$\alpha_4 \text{Competitive\_Spread}_{ti} + \alpha_5 \text{Normalized\_Price}_{ti} + \varepsilon_{ti} \qquad (5)$$

The normalized price variable allows us to compare the price effects across countries as it reflects the effect of price evolution over time within a category. While there are absolute price differences across countries, the main effect of such differences is picked up by country-specific random intercepts. The effect of price evolution will be estimated using the Normalized_Price variable. We do not expect this effect to differ across countries (α_5 is assumed invariant across countries). The direct effects of Marketing Breadth and Competitive Spread on category sales are assumed to be common across countries. However, we assume that the variables of interest have country-specific effects on the growth rate as per the structure shown in Equation (8) which we discuss below.

Note that parameter Φ_{ti} reflects the diffusion of the category as in Shankar (1999). If category sales are growing over time, then Φ_{ti} is positive. Therefore, Φ_{ti} measures the growth rate of the category, i.e., the higher is the value of Φ_{ti}, the faster sales are growing. To illustrate, consider a hypothetical example where $\Phi_{ti} = \Phi$, i.e., does not change over time. We can then write Equation 6 which reflects the growth rate in sales from *t* to time *t+1* assuming that other factors which affect sales are constant:

$$\ln(S_{t+1}) - \ln(S_t) = \frac{\Phi}{t(t+1)} \qquad (6)$$

When Φ is positive (sales grow) and the higher is its value, the larger is the difference between S_{t+1} and S_t. Figure 2 demonstrates category sales for our hypothetical example of constant Φ_{ti}.

Insert Figure 2 about here

Returning to our model, the parameter Φ_{ti} is a measure of how the "baseline sales" of the category grow over time. Our interest is to assess the manner by which the growth rate is influenced by the Marketing Breadth and Competitive Spread. In summary, our earlier discussion implies that a) the effect of Marketing Breadth on growth rate might be moderated by the number of competitors and b) the effect of Competitive Spread on the growth rate might be moderated by

the total level of marketing spending in the category. Accordingly, to assess these conjectures, we decompose the growth rate parameter as follows:

$$\Phi_{ti} = \beta_{i0} + \beta_{ti1}, \tag{7}$$

$$\beta_{ti1} = (\gamma_0 + \gamma_1 \text{Few}_{ti})\text{Mktg\_Breadth}_{ti} + (\gamma_2 + \gamma_3 \ln(\text{TotalMktg}_{ti}))\text{Competitive\_Spread}_{ti} \tag{8}$$

When there are few competitors in the market, $\text{Few}_{ti} = 1$ and the impact of marketing breadth is reflected by $\gamma_0 + \gamma_1$. When there are many competitors, $\text{Few}_{ti} = 0$ so the impact is measured by γ_0.

Similarly, the impact of Competitive_Spread when the logarithm of TotalMktg_{ti} equals zero is reflected by γ_2 ; we test whether this effect is moderated by total marketing spending within the category, which is reflected by γ_3. The nature of our data is hierarchical with units defined at time t within a country. Accordingly, we use a hierarchical linear model specification to capture the potential heterogeneity of coefficients across countries. More specifically, the sales response function in Equation (4) and its transformed version, Equation (5), is the first level. The second level (across countries) is described by the following distributions:

$$\alpha_{i0} = \alpha_0 + v_{i0}, \text{where } v_{i0} \sim N(0, \tau_0)$$
$$\alpha_{i1} = \alpha_1 + v_{i1}, \text{where } v_{i1} \sim N(0, \tau_1)$$
$$\alpha_{i2} = \alpha_2 + v_{i2}, \text{where } v_{i2} \sim N(0, \tau_2)$$
$$\beta_{i0} = \alpha_3 + v_{i3}, \text{where } v_{i3} \sim N(0, \tau_3)$$

The ARB drug category is ideal for our analysis: the first product was launched in 1995, coinciding with the start of our dataset. By 2010, there were more than 8 competing brands in each category in most countries. This means that the category is well aligned with our data requirement: a category from its beginning to maturity. We first focus on the ARB data for our model estimations. Data from EDD and statins are used to further examine the robustness of our model findings. Our investigation of the values (and significance) of γ_0, γ_1, γ_2 and γ_3 can be assessed because of the variability in growth rates and competitive environments provided by multilevel observations. Observations across several countries reflect competitive structure heterogeneity. Although the product categories do exhibit overlap across the category life cycle, there are clear differences in their coverage. The statins 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 does not correspond to the introductory period. Similarly, the EDD category had not

reached full maturity in 2010 (the last observations in the data set are from 2010). In fact, in 2010, there were only 4 brands approved by FDA in the EDD category.[7] 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 examining the parameters for each category individually. In particular, we contrast the results of the ARB category where we have complete data for each country with the other product categories that only cover part of the product life cycle.

Three issues emerge when estimating a model of market growth at the industry level. The first one is autocorrelation. To assess the existence of autocorrelation in the data, we ran Lagrange multiplier tests on the data. In 14 out of the 21 category-markets, autocorrelation exits (Table 1). In our estimation, we control for autocorrelation.

Insert Table 1 here

The second issue in estimation is potential endogeneity between the detailed patterns of marketing spending (namely marketing breadth and competitive spread) and market growth. Our approach to control for this possible endogeneity is to implement a two-stage estimation. In a first stage, we use exogenous variables as instruments to predict the potentially endogenous variables (i.e., Marketing Breadth and Competitive Spread). The variables include industry structure variables (e.g., number of competitors) and lagged variables. Seemingly unrelated regression is used due to the simultaneity of "marketing breadth" and "competitive spread":[8]

$$\begin{cases} \text{Mktg\_Breadth}_{ti} = \theta_{0i} + \theta_{1i}\,ln(S_{t-1,i}) + \theta_{2i}\,ln(\text{ncomp}_{t-1,i}) + \theta_{3i}\text{Mktg\_Breadth}_{t-1,i} + \theta_{4i}\text{Competitive\_Spread}_{t-1,i} + \delta_{t-1,i} \\ \text{Competitive\_Spread}_{ti} = \lambda_{0i} + \lambda_{1i}\,ln(S_{t-1,i}) + \lambda_{2i}\,ln(\text{ncomp}_{t-1,i}) + \lambda_{3i}\text{Mktg\_Breadth}_{t-1,i} + \lambda_{4i}\text{Competitive\_Spread}_{t-1,i} + \zeta_{t-1,i} \end{cases}$$

$$(9)$$

In a second stage, we then use the *predicted* "Marketing_Breadth" and "Competitive_Spread" to estimate the hierarchical linear model. We cannot identify a theoretical basis to explain why the instruments of equation (9) might be correlated with the error terms of equation (5). Second, the quality of the instruments is confirmed by checking the R-square for the two predictor equations

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[7] 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.

[8] Although the errors of each equation can be correlated because of the simultaneous system, Breadth and Mkt_Spend_Conc are not endogenous to the system of equations (they are only affected by lagged values of the other variables). Consequently, SUR estimates are appropriate.

in (9). The R squares for the instrumented variables are presented in Table 2 and seem satisfactory.

Insert Table 2 here

The estimation of the hierarchical model is performed using the EM procedure in Stata.

In order to account for the potential endogeneity of total marketing (in addition to Marketing Breadth and Competitive Spread), we re-estimate the model with instrumented values for total marketing as well as for Marketing Breadth and Competitive Spread. The possibility of this being a problem as a category passes through the stages of the PLC is mentioned in Bronnenberg et al. (2000). The re-estimated model generates similar results except for one parameter in the ARB category which is insignificant. Hence, we conclude that category marketing spending does not suffer from endogeneity and we report the estimation where only Marketing Breadth and Competitive Spread are instrumented. The results for the estimation when the instrumented value of total marketing is used in equation (5) are available from the authors.

The third issue in estimating a model of market growth is the potential collinearity among explanatory variables. We use Lasso estimation to examine the collinearity and potentially model selection (Gelper and Stremersch 2014). The Lasso estimation applies a shrinking process where it penalizes the coefficients of the regression variables by shrinking some of them to zero. During the process, the variables that still have a non-zero coefficient after the shrinkage are selected to be part of the model. We include the variables in our model, as well as variables in our dataset and some of their functional transformation. To be more specific, the extra candidate variables we put in the Lasso estimation are: Total_Marketing, Detailing, Mail, Journal_ads, DTCA, Number of competitors, B2B ads, the degree of competitive spread within detailing, the degree of competitive spread within mail, the degree of competitive spread within journal ads, the degree of competitive spread within DTCA, $\text{Mktg\_Breadth}_{t-1}$, $\text{Competitive\_Spread}_{t-1}$, $\ln(\text{Total\_Mktg}_{t-1})$, $\ln(\text{number of competitors}_{t-1})$, and $\ln(s_{t-1})$. Table 3 shows the results for each category where variables are not zero in the Lasso estimation. A first observation from the Lasso estimation results is that, among the variables chosen by Lasso process, $\text{Competitive\_Spread}_t$, $\text{Competitive\_Spread}_{t-1}$, Spread of Detailing, Spread of Mail, Spread of Journal_ads, and Spread of DTCA all contribute to the sales significantly. This suggests that the effect of Competitive Spread must be included in our model and deserves our attention. The

second observation is that lagged variables are important to explain category sales. This is consistent with concerns we have regarding autocorrelation and endogeneity and it provides support for our use of predicted variables in equation (9). The last observation is that the Lasso estimation chooses ln(Total_Mktg) instead of Total_Mktg; this supports our choice of the functional form in equation (6).

Insert Table 3 here

7   Estimation results

First, we consider the ARB category for which the data covers the introductory period to early maturity. We start by reporting our estimation findings for the ARB category in Table 4. As noted earlier, we instrument for marketing breadth and competitive spread recognizing the fact that the decisions of managers, in terms of how they allocate marketing resources, might be affected by the growth rate of previous periods. [9]

Insert Table 4 here

The first observation from the results is that the estimated coefficients of the control variables (i.e., "total marketing spending", "Few", and "normalized price") are consistent with our expectations, even though they are not the focus of this study. In particular, more competitors tend to increase overall category sales ($\alpha_2 < 0$, recall that Few=0 if there are more than 4 competitors). The coefficient of marketing spending (α_1) is positive. Furthermore, price's impact on sales is marginally significant, albeit the sign is as expected in that higher prices tend to decrease sales ($\alpha_5 < 0$).

The second observation relates to the main effects of the key variables of interest, i.e., Marketing Breadth and Competitive Spread. The direct effect of Marketing Breadth on sales (α_3) is positive and significant, which means broader spending across different marketing levers tend to increase sales. However, α_4, the coefficient of Competitive Spread, is not significant.

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[9] We provide the results of the first stage estimation where instead of using the instrumental variables to address endogeneity, only original variables are used (Table 8). The growth rate decomposition parameters are affected, which underlines the need to correct for endogeneity.

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

$$\Phi_{ti} = \beta_{i0} + (\gamma_0 + \gamma_1 \text{Few}_{ti})\text{Mktg\_Breadth}_{ti} + (\gamma_2 + \gamma_3 \ln(\text{TotalMktg}_{ti}))\text{Competitive\_Spread}_{ti} \quad (10)$$

In the above equation, Φ_t is the overall category growth rate. The parameter β_0 measures the base level growth of the category and the estimates of β_0 are significant and positive ($\beta_0 = 19.60$). A positive base level growth rate is consistent with the model specification.

As noted earlier, the growth rate is affected by industry level marketing activities but our primary interest is the decomposition of the growth rate. Replacing the coefficients in Equation (6) with the estimates of Table 4, we have:

$$\beta_{ti1} = (20.80 - 21.30\text{Few}_{ti})\text{Mktg\_Breadth}_{ti} + (-15.39 + 1.75 \ln(\text{TotalMktg}_{ti}))\text{Competitive\_Spread}_{ti}$$

$$(11)$$

The first item on the right-hand side of Equation (9) supports the idea that when there are many competing firms in the market (Few=0), broader marketing spending increases market growth ($\gamma_0 = 20.80$). However, when there are only a few competitors (Few=1), the impact of broader spending is strongly moderated ($\gamma_1 = -21.30$). The overall effect of marketing breadth on the growth rate when there are few competitors is insignificant and the estimated sign is negative ($\gamma_0 + \gamma_1 = -0.50$).

The second item in Equation (9) concerns the effect of "Competitive Spread", which is negative ($\gamma_2 = -15.39 < 0$). This means that higher competitive spread decreases the category growth rate. In other words, when the market is characterized by a wide participation in marketing from many firms, the category actually grows more slowly. Furthermore, we also find that $\gamma_3 = 1.75 > 0$. This means that a higher level of total marketing spending reduces the effect of competitive spread. It seems that low levels of competitive spread when the level of total marketing spending is relatively low, allows individual competitors to operate in the part of the response curve where physicians respond to marketing effort (Lilien et al. 1992). However, as marketing spending levels increase, low levels of competitive spread have a reduced effect on category growth. We believe that an explanation for this finding is based on how the role of marketing changes as a category matures. As a category matures, an increased fraction of marketing spending is dedicated to business stealing as opposed to category expansion. When two firms spend against each other to "steal business" the effects may cancel each other out. We postulate that high levels of competitive spread when total category spending is high lead to lower

levels of "cancelling out". This explains the reduced effect of spread on category growth at high category spending levels.

Because both ln(TotalMktg) and Competitive_Spread are continuous variables, we conduct a floodlight analysis to further examine the robustness of our estimates. The results are provided in Table 5.

Insert Table 5 here

The floodlight analysis of the ARB category suggests that higher Competitive_Spread can impede the category growth at low levels of TotalMktg providing further support for the idea that more concentrated spending (by individual firms) is essential to activate new customers.

It is interesting to note that in the ARB category, the value of ln(TotalMktg) ranges from 6.14 to 11.52. The floodlight analysis also suggests that when the total marketing spending is high, i.e., ln(TotalMktg) larger than the mean value, higher competitive spread may increase category growth.

To further examine the validity of the model, we turn to our remaining categories: EDD and statins. The estimation results for the analysis of the EDD and statin categories are provided in Table 6.

Insert Table 6 here

The estimates from the EDD data exhibit qualitatively similar results. Here γ_0=12.25 and γ_1 = -11.59. A positive γ_0 confirms that broader marketing spending increases category growth when there are many competitors. This supports our Hypothesis 1. Further more, the other result obtained in the ARB category "that marketing breadth can slow category growth" when there are few competitors is also supported by the negative γ_1. We do however, find that the impact of marketing breadth (α_3) becomes insignificant. Meanwhile, the finding that higher price leads to lower sales is confirmed by a significant estimate (α_5<0). In fact, when Few=1, $\gamma_0 + \gamma_1 = 0.66$. While 0.66 is not statistically significant, it reinforces the idea that broad marketing spending does not accelerate category growth when there are few competitors.

The estimate of γ_2 =-5.59 implies that the direct impact of higher competitive spread on the category growth is negative. We also note that $\gamma_3 = 0.75$. This means that as spending level increases, the impact can become positive. In the EDD data, the value of ln(TotalMktg) ranges from 3.59 to 12.03. Because competitive spread and spending level jointly affect category growth,

we examine their overall impact through floodlight analysis. At the minimal value of $\ln(\text{TotalMktg})$, we find that higher competitive spread decreases category growth ($-5.59 + 0.75 \times 3.59 < 0$). This negative impact on growth rate is consistent with the results in ARB category. We also note that in the floodlight analysis, the effect of competitive spread on market growth becomes insignificant as the level of marketing spending increases.

The difference in the floodlight analysis between EDD and ARB is in all likelihood due to the competitive environment in the EDD category. Through 2010, three major PDE5 inhibitor brands (Viagra, Cialis, Levitra) dominated marketing spending in the category. As noted earlier, we conjecture that "as a category matures, more firms enter and engage in competitive marketing activities". However, as of 2010, it is difficult to classify the EDD market as having matured. The market is dominated by three oligopolistic firms that have learned "how to compete with each other" (i.e., the firms limit the quantity of marketing resources to avoid head-on competition). This may explain why higher level in marketing spending does not revert the impact of competitive spread on EDD category growth.

The estimates of the direct effect of the explanatory variables in the statin category are similar to the results for the ARB and EDD categories. The estimates of Price and the baseline growth rate (β_0) are significant and similar to our previous estimations. The estimates of α_2 and γ_1 are significant yet some caution should be exercised in interpreting these parameters. By 1995, the earliest date of our data, there were already more than 8 statin brands in most countries and as a result, only 8 obervations have "Few=0". The estimates from these eight observations may not be sufficient to interpret the parameters with confidence. To further check the robustness of the results regarding the statins category, we re-estimated the model without these 8 observations where Few=0, and the estimates are identical in terms of signs and significance level. Apart from these variables, all other estimates showed no significance, including our measure on Marketing Breadth and Competitive spread. We also estimated the model with a variable "ncomp" (the number of competitors), and obtained similar results, i.e., only Price and the baseline growth rate are significant. In conclusion, the statin market was already a well-established category by 1995. The market is characterized by more than 8 major brands, tens of small brands, as well as numerous generics[10]. In a market with such stabilized and crowded competitive environment, firms sell to the same set of customers, the marketing efforts from one firm are easily negated by the efforts from others. This cancelling out effect makes marketing spending insignificant both in terms of sales and in terms of category growth. Consequently, sales are mostly driven by the

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[10] We combine the sales and marketing spending data of all generics and treat them as one brand: generics.

baseline growth rate and price competition. These results from the statin category, combined with the results from ARB and EDD categories support Hypotheses 5 and 6.

In conclusion, the model produces similar results across different categories although with varying degree of significance. Our analysis provides evidence for the nuanced effect of Marketing Breadth and Spending Concentration over the full range of the Product Life Cycle. The introduction stage of the PLC is represented in the context of two categories (ARB and EDD, the growth stage by three categories (Statins, ARB and ADD) and the maturity stage by two categories (ARB and Statins).

A Distinct Cut-Off versus the Number of Competitors

As discussed in Section 3.1, we consider two alternatives to reflect the "competitiveness" of the category. To maintain internal consistency, we focus on the one category for which the data cover all stages of the Product Life Cycle (Introductory, Growth and Maturity), the ARB category. In addition, ARB is the one category where the number of competitors grows from one to more than nine and higher in some countries. We first estimate a model where the variable "Few" in equations (5) and (8) is replaced by the number of competitors. The results pertaining to "number of competitors" were insignificant, though the signs of the estimated coefficients were as expected.

To investigate the distinct cut-off formulation, we evaluated several levels for the threshold. Table 7 summarizes the estimates under different specifications of "Few".

Insert Table 7 about here

We find that the effects are most significant when "Few" is defined at a threshold of four or more competitors. This echoes the discussion of Section 3.1 and provides an argument for using thresholds as a basis for determining the feasibility (or likelihood) of collusive behavior in pharmaceutical markets.

8   Discussion

The primary goal of this research is to offer insight about factors that explain the growth rates in new product markets as they evolve over time from the introductory stage, through the growth stage and finally into maturity. Our focus is on factors that characterize the nature of competitive

interactions within a category. This builds on the axiom that competitive dynamics are a fundamental determinant of how markets evolve and grow (Soberman and Gatignon 2005). Using data from the pharmaceutical industry, our study provides useful insight about this relationship in the context of international marketing.

The product categories we study are for the most part, the only solution (or treatment) for a specific class of therapeutic problems. As a result, the impact that the *pricing and marketing actions of other substitutes/drugs* 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 of all major marketing levers that firms use to promote the sale (and use of) these products. As a result, there is less unexplained variance and this helps us to uncover the relationships we wish to analyze. There are two major factors about our approach that help our analysis to generate insights that are both general and robust about the diffusion of new products.

First, the pharmaceutical categories we have chosen 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 analyze 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 critical. The relationships that interest us focus on how competitive dynamics affect market growth from the introductory stage of a pharmaceutical category until maturity.

Second, a key challenge with an analysis like this is the endogeneity of independent variables such as the breadth of marketing spending and spending concentration. In particular, it is well known that companies often have policies that depend on sales performance or market share levels observed in past periods. Moreover, forecasted numbers are invariably estimated utilizing historical trends and past sales. Thus, a key challenge when analyzing such relationships is to account for this endogeneity in the estimation and to determine whether the postulated relationship is evident. Because of the nature of our data (which is longitudinal and contains a number of exogenous variables), we correct for this problem with a 2-stage estimation wherein predicted estimates of the variables subject to endogeneity (generated with instrumental variables) are used to assess the relationships.

In sum, the two factors above are critical. They facilitate a careful assessment of the relationships we believe are important drivers of category growth.

9   Conclusion

Our objective was to understand how competitive marketing activities, namely the breadth of marketing spending across different marketing mix variables and the degree of competitive spread impact the evolution and growth of primary demand over time.

First, our analysis shows that the two constructs, Marketing Breadth and Competitive Spread are distinct and have very different effects on market growth. While both are measures of spread, their impact on market growth are opposite and thus should be carefully distinguished by academia and marketing practitioners. The analysis shows that when there are few competing firms in the market (as is the case early in the life of a category), a high degree of Marketing Breadth reduces market growth. The analysis suggests that broad marketing spending makes it difficult for new entrants to build momentum (it may even deter potential entrants from launching). This obtains because, on average, tacit (or explicit) collusion allows firms to make entry either unattractive or difficult for potential entrants. Consistent with industrial organization theory (Fraas and Greer 1977) however, this becomes less feasible as the number of competitors increases. When there are many firms, we find that broad marketing spending performs the expected role of increasing the number of customers (in this case, prescribing physicians). This expands the market and is reflected in higher levels of category growth.

We also find that market growth is closely related to (and influenced by) the degree of competitive spread. To be specific, when marketing spending is relatively low, spread spending (by many firms) impedes category growth. This further confirms that firms spend less than optimal for the category to grow, and this under-spending even outweighs the increased market coverage by a higher number of participating firms in the market. However, as the total level of spending increases, the marginal effectiveness of marketing to activate new customers increases. And this effect is further strengthened if more firms participate in marketing (higher competitive spread).

Last, when a category reaches full maturity, a greater fraction of marketing is dedicated to "business stealing" and this leads to high levels of cancelling-out. Accordingly, neither marketing breadth nor competitive spread has any impact on category sales and market growth. Pricing remains a significant contributor to overall market sales. This highlights that in a mature market, information is well disseminated and the main driver of the customer participation comes from price.

Our findings provide useful insight for both the production and operations managers and marketing managers who are responsible for the allocation of operational and marketing resources in categories at different stages of market evolution. First, in the early growth stage of

a category, our research provides two strong arguments for firms to carefully coordinate their effort in operation and marketing. Not only does broad marketing increase awareness of the category across diverse user segments, it also makes it difficult for entrants (or smaller firms) to gain a foothold and reach critical mass. This suggests that a multi-product line strategy may actually help the category growth in the early stage of a product life cycle. Second, as categories mature and the number of competitors increases, managers need to measure and assess the impact of marketing. Our analysis documents a general reduction in the ability of marketing to stimulate growth as a market matures due to a). a reduced number of potential "new" users and b). the cancelling out effect of competitive marketing efforts. Thus, an assessment of marketing's ability to "steal business" as well as stimulate category growth is essential from the perspective of individual companies. Production efficiency and cost advantage are critical in this stage of life cycle. Finally, our findings provide empirical support for analysts of collusive conduct in oligopolistic industries. While in theory, any number of firms can collude, our analysis suggests that tacit collusion is unlikely in a category with four or more competitors.

To conclude, our work provides a basis to elucidate the complex relationship between the competitive dynamics of a category and the rate at which this category expands. The analysis confirms a number of insights about markets that are based on a combination of ideas derived from industrial organization and from diffusion theory

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Figure 1: Conceptual Framework
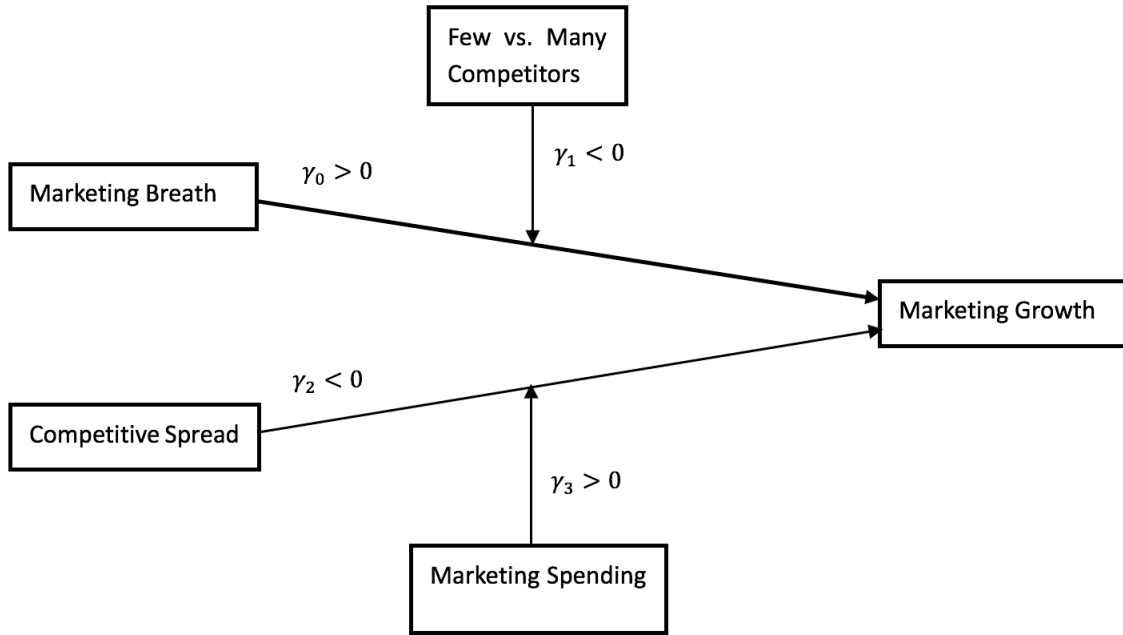
Figure 2: Examples of Market Growth Rates as a Function of Parameter Φ
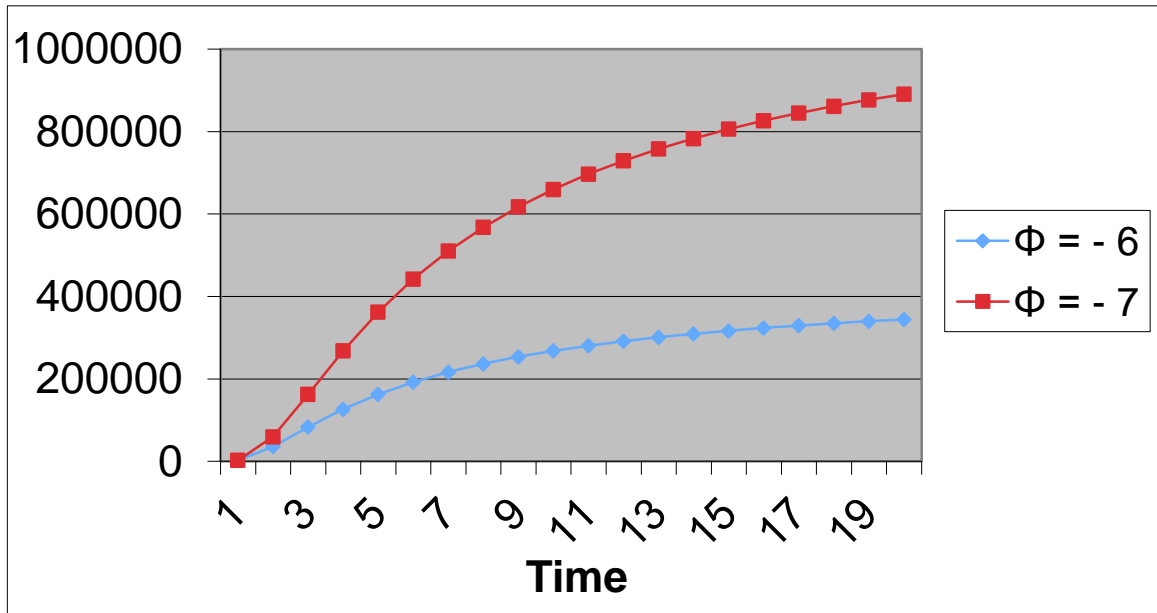
Table 1: Lagrange multiplier tests of autocorrelation

Country	Category		
	ARB - x^2	EDD $- x^2$	Statin $- x^2$
Canada	0.249	1.566	10.355**
France	8.252**	0.740	9.503 **
Germany	10.957***	17.241 ***	0.119
Italy	3.279*	0.003	1.600
Spain	9.941**	0.032	2.888 *
UK	12.459 ***	2.627	4.016 **
US	9.761 **	1.225	17.125 ***

Table 2: The R^2 of the Instrumentation Equations

	R^2
Mktg_Breadth	0.774
Competitive_Spread	0.860

Table 3: The Lasso estimates of the explanatory variables

	Category		
Parameters	ARB	EDD	Statins
$1/t$ (β_0)	-2.837	-2.710	-88.199
Mktg_Breadth/t (γ_0)	2.222	N/A	-51.520
Mktg_Breadth*Few/t (γ_1)	-1.982	N/A	64.931
Competitive_Spread/t (γ_2)	-9.436	-4.442	62.628
$\ln(\text{TotalMktg}) *$ Competitive_Spread/t (γ_3)	0.298	N/A	0.241
$\ln(\text{TotalMktg})$ (α_1)	0.49	0.249	0.020
Few (α_2)	0.264	N/A	-0.618
Mktg_Breadth (α_3)	-3.459	0.049	-0.743
Competitive_Spread (α_4)	0.182	0.541	-1.402
Normalized_Price (α_5)	-0.084	-0.634	-0.324
mail	N/A	-0.001	-0.0001
Number of competitors	0.021	0.014	0.010
Spread_detailing	0.616	0.018	-0.492
Spread_mail	0.038	-0.099	0.037
Spread_journal	0.010	0.017	0.204
Spread_DTCA	-0.055	-0.589	-0.396
Mktg_Breadth$_{t-1}$	-0.235	N/A	-0.186
Competitive_Spread$_{t-1}$	1.116	0.142	-0.055
$\ln(\text{TotalMktg}_{t-1})$	-0.134	-0.020	0.032
$\ln(\text{number of competitors}_{t-1})$	-0.988	-0.515	-0.384
$\ln(S_{t-1})$	0.774	0.538	0.562
Intercept (α_0)	3.890	3.623	8.555

Table 4: Estimates of the Parameters for the Model of Equations 5, 7 and 8

Category	ARB	
Parameters	Estimate	Standard Error
Intercept (α_0)	11.66***	0.451
ln(TotalMktg) (α_1)	0.11***	0.029
Few (α_2)	-0.94***	0.126
Mktg_Breadth (α_3)	0.49***	0.119
Competitive_Spread(α_4)	0.06	0.099
Normalized_Price (α_5)	-0.18	0.167
1/t (β_0)	19.60***	5.936
Mktg_Breadth/t (γ_0)	20.80***	2.497
Mktg_Breadth*Few/t(γ_1)	-21.30***	2.299
Competitive_Spread /t (γ_2)	-15.39***	2.674
ln(TotalMktg) $*$ Competitive_Spread/t (γ_3)	1.75***	0.336

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

<p align="center">**Table 5: Floodlight analysis**</p>

	ARB		EDD		Statins	
	estimate	std. err.	estimate	std. err.	estimate	std. err.
$\gamma_2 + \min * \gamma_3$	-4.61***	0.714	-2.87**	1.252	6.08	7.860
$\gamma_2 + (\text{mean} - \text{sd}) * \gamma_3$	0.06	0.528	-0.59	1.068	5.88	7.322
$\gamma_2 + \text{mean} * \gamma_3$	2.08**	0.822	0.57	1.466	5.78	7.901
$\gamma_2 + (\text{mean} + \text{sd}) * \gamma_3$	4.10***	1.171	1.74	1.997	5.68	8.942
$\gamma_2 + \max * \gamma_3$	4.81***	1.298	3.48	2.877	5.54	10.800

Legend
Min=minimum (ln(TotalMktg))
Max=maximum (ln(TotalMktg))
Mean=mean (ln(TotalMktg))
sd=standard deviation (ln(TotalMktg))

Table 6: Estimates of the EDD and statins category

Category	EDD		Statins	
Parameters	estimate	std. err.	estimate	std. err.
Intercept (α_0)	8.87***	0.400	14.12***	0.347
ln(TotalMktg) (α_1)	0.15***	0.031	0.04	0.028
Few (α_2)	-0.45*	0.238	0.40***	0.010
Mktg_Breadth(α_3)	0. 10	0.179	-0.29	0.196
Competitive_Spread(α_4)	0.21	0.137	0.06	0.182
Normalized_Price (α_5)	-1.42***	0.160	-0.26***	0.030
1/t (β_0)	26.57***	8.693	109.77***	11.192
Mktg_Breadth/t (γ_0)	12.25***	3.881	-12.56	10.202
Mktg_Breadth*Few/t (γ_1)	-11.59***	3.664	16.22**	6.505
Competitive_Spread/t (γ_2)	-5.59**	2.489	6.61	15.788
ln(TotalMktg) * Competitive_Spread/t (γ_3)	0.75*	0.416	0.08	1.747

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

Table 7: 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	Coef	std. err	Coef	std. err	Coef	std. err	Coef	std. err	Coef	std. err
α_0	11.57***	0.554	11.86***	0.459	11.66***	0.451	11.64***	0.480	11.67***	0.534	11.69***	0.499
α_1	0.13***	0.038	0.09***	0.030	0.11***	0.029	0.11***	0.029	0.10***	0.031	0.11***	0.031
α_2	-0.62***	0.155	-0.90***	0.091	-0.94***	0.126	-0.85***	0.101	-0.49***	0.097	-0.38**	0.183
α_3	0.14	0.112	0.22**	0.110	0.49***	0.119	0.37***	0.112	0.22*	0.112	-0.10	0.139
α_4	0.10	0.110	0.25***	0.095	0.06	0.099	0.04	0.102	0.14	0.103	0.12	0.101
α_5	-0.27	0.174	-0.25	0.165	-0.18	0.167	-0.19	0.170	-0.24	0.176	-0.22	0.172
β_0	22.31***	6.058	22.09***	5.903	19.60***	5.936	19.41***	6.031	20.38***	5.921	22.13***	6.048
γ_0	7.82***	1.670	10.15***	1.763	20.80***	2.497	18.79***	2.375	14.54***	2.361	4.21	4.014
γ_1	-10.25***	1.427	-11.99***	1.629	-21.30***	2.299	-19.16	2.149	-15.08***	2.134	-6.32*	3.359
γ_2	-20.18***	2.944	-17.80***	2.619	-15.39***	2.674	-14.87***	2.694	-15.34***	2.814	-20.47***	2.847
γ_3	2.30***	0.357	2.04***	0.329	1.75***	0.336	1.71***	0.338	1.79***	0.353	2.38***	0.354

Table 8: First stage estimates without instrument variables

	ARB		EDD		Statins	
	Coef	std. err	Coef	std. err	Coef	std. err
α_0	11.32***	0.617	8.77 ***	0.410	14.11***	0.264
α_1	0.05	0.035	0.14***	0.036	0.04***	0.013
α_2	-0.23	0.182	-0.49*	0.260	0.43***	0.091
α_3	-1.01***	0.355	-0.73**	0.284	-0.23	0.247
α_4	1.12***	0.248	0.13	0.184	0.05	0.227
α_5	-0.24	0.185	-1.07***	0.143	-0.27***	0.029
β_0	15.86***	5.291	27.77***	7.645	107.68***	11.491
γ_0	5.00	3.474	-2.87	3.495	-11.84	8.233
γ_1	-8.58**	3.396	-10.41***	2.580	17.26***	5.876
γ_2	7.03***	1.023	3.73***	1.117	9.16	8.943
γ_3	-0.14***	0.040	-0.05	0.045	-0.01	0.024