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Patient- or Physician-oriented Marketing: What Drives Primary Demand for Prescription Drugs?

Marc Fischer and Sönke Albers

What are the market-expanding effects of direct-to-consumer versus physician-oriented advertising? Using a new method that aggregates data at the brand level, Fischer and Albers examine 86 categories in the U.S. pharmaceutical market. Their findings offer important marketing and public policy implications.

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Report Summary

Since 1997, when the Food and Drug Administration relaxed restrictions targeting advertising to patients, expenditures on direct-to-consumer (DTC) advertising have tripled, from U.S. $1.1 billion in 1997 to U.S. $3.3 billion in 2005.

While DTC advertising for prescription drugs provides new opportunities for marketers, health care professionals and policymakers debate the value of such patient-oriented marketing efforts. For example, policymakers and insurers argue that DTC advertising expands demand for expensive, branded products and therefore inflates health care costs. Physicians suggest further that patient-oriented marketing efforts may create demand for potentially dangerous products. What are the market-expanding effects of DTC advertising as compared to advertising directed at physicians?

In this study, authors Fischer and Albers analyze the effects of marketing efforts directed at patients through DTC advertising versus marketing efforts directed at physicians through detailing (personal contact by sales representatives) or professional journal advertising. They suggest a new method for measuring primary demand effects with aggregate data at the brand level and apply their model to 86 categories of the U.S. pharmaceutical market from 2001-2005.

They find that physician-oriented marketing efforts such as detailing are effective in increasing primary demand, that is, in expanding the market rather than substituting sales from competitors. In contrast, patient-oriented marketing efforts such as DTC show negligible effects on primary demand. However, DTC advertising appears to be quite effective in stealing sales from competitive brands.

From a marketing standpoint, these findings suggest that managers should carefully analyze the potential countereffects of a DTC campaign. If competitors retaliate to that campaign by increasing their DTC expenditures, the net sales effect could be zero, with a negative impact on profit.

From a public policy standpoint, DTC advertising does not appear to increase demand for products that may be potentially dangerous. However, the effectiveness of detailing suggests that this type of marketing effort may provide incentives to physicians to prescribe drugs that are not required from a medical perspective. In such cases, health care costs rise, with negative consequences for social welfare. ■

Introduction

In 1997, the Food and Drug Administration (FDA) relaxed restrictions on drug advertising that targets patients. This policy change resulted in a considerable rise in spending on direct-to-consumer advertising (DTC) in the following years. According to IMS Health, expenditures tripled from U.S. $1.1 billion in 1997 to U.S. $3.3 billion in 2005. While the industry appears to be excited about the new marketing opportunities, many professionals in the health care industry cast serious doubts about the usefulness of DTC (e.g., Hollon 1999; Wilkes, Bell, and Kravitz 2000; Wolfe 2002). Policymakers and insurers argue that DTC expands demand for expensive, branded products that may easily be substituted by cheaper alternatives such as generics and therefore inflates health care costs. Physicians fear that DTC may create demand for a potentially dangerous product that would have not existed otherwise. The quantification of a potential market-expanding effect of DTC is therefore of paramount importance to health care professionals, politicians, and managers.

DTC, or patient-oriented marketing, appears to be an important new element of pharmaceutical marketing; however, it is not the only one. Marketing efforts directed at physicians still account for the lion's share of the marketing budget. These efforts include personal selling activities by sales representatives (detailing), advertisements in medical journals (professional journal advertising), and other marketing expenditures (OME) such as physician meetings or dinner invitations. Information mediated through these activities is more specific than that provided in DTC campaigns. Physicians become aware of new therapeutic alternatives. They learn about alternative ways to diagnose a disease that increase the number of diagnosed patients within the population. As a result, physician-oriented marketing efforts may also expand the demand for a pharmaceutical product.

Consistent with the literature (e.g., van Heerde, Gupta, and Wittink 2003), we define the term *primary demand* as demand that affects the *market size*, while *secondary demand* changes only *market share* but not total sales of the market. While there are good arguments for the existence of primary demand effects with respect to both patient- and physician-oriented marketing, we do not know which type of pharmaceutical marketing has a larger impact. A growing body of literature deals with the effects of pharmaceutical marketing (see the excellent review on physician-oriented marketing by Manchanda and Honka 2005), but only a small portion of that addresses primary demand effects. Interestingly, the majority of relevant studies focuses on the primary demand effect of DTC (e.g., Calfee, Winston, and Stempski 2002; Iizuka and Jin 2005; Narayanan, Desiraju, and Chintagunta 2004). The results from the available studies, however, are not uniform. While some point to the existence of a market expansion effect for DTC (e.g., Iizuka and Jin 2005; Narayanan, Desiraju, and Chintagunta 2004), others do not find a significant relationship (e.g., Calfee, Winston, and Stempski 2002). The picture does not change much with respect to physician-oriented marketing. Studies on primary demand effects in this area are particularly sparse, and the results are again inconclusive. Moreover, the empirical evidence with regard to professional journal advertising is based on just *one* product market.

Hence, we identify a need for more research to measure primary demand effects of patient- and physician-oriented marketing. Although existing research provides valuable insights, it is also subject to several limitations. First, the majority of studies involve only a few selected product categories. Empirical generalizations are difficult to obtain from these samples. Second, the conventional approach to measuring primary demand effects is to specify and estimate a category sales model. However, the use of highly aggregated data at the category level ignores the fact that some brands are

more effective in driving primary demand than others. As a consequence, a category sales model tends to understate primary demand responsiveness. Third, some findings of prior research may be biased because these studies failed to account for heterogeneity across categories and/or endogeneity.

The empirical contribution of this study is to provide generalizations of the primary demand effects of DTC and the two most important physician-oriented marketing elements, detailing and professional journal advertising. We study 86 product categories of the U.S. pharmaceutical market in the years 2001 through 2005. Our analysis reveals differences in primary demand effects across categories that can be explained by a number of moderating variables. Unlike previous studies, our study also separates primary demand effects into short-term and long-term effects. In addition to the empirical contribution, we provide a methodological contribution by developing a new method for estimating primary demand effects with aggregate data at the brand level instead of the category level. We employ an estimation methodology that controls for brand and category heterogeneity and potential endogeneity of marketing mix variables. Hence, the results do not suffer from estimation bias.

In the next section, we review the related literature. We then develop our methodology to estimate the primary demand effect. We continue with a discussion of estimation issues and the description of the dataset, followed by our results. The paper concludes with a discussion of the findings, implications, and the limitations of the study.

Literature Review

Primary demand effects of pharmaceutical marketing

The effects of pharmaceutical marketing have recently attracted the attention of researchers (e.g., Berndt et al. 1995; Chintagunta and Desiraju 2005; Wittink 2002). A number of studies have also investigated primary demand effects. Table 1 summarizes the main characteristics and findings of these papers.

Five out of seven studies report a primary demand effect of patient-oriented marketing. Most studies find a significant, albeit small, primary demand elasticity of around .02. In contrast to these studies, Calfee, Winston, and Stempski (2002) do not find evidence that DTC influences primary demand. Four studies considered the primary demand effects of physician-oriented marketing. Chintagunta and Desiraju (2005) and Narayanan, Desiraju, and Chintagunta (2004) do not find an effect of detailing in selected product markets. In contrast, the analysis of other product markets revealed a small primary demand elasticity of around .03 (Chintagunta and Desiraju 2005; Rosenthal et al. 2003). The studies by Narayanan, Desiraju, and Chintagunta (2004) and Rosenthal et al. (2003) encompass both physician-oriented and patient-oriented marketing. Their results suggest that patient-oriented marketing is the main force driving primary demand. The study by Berndt et al. (1995), however, contrasts with this conclusion. The authors analyzed the development of the antiulcer category over 17 years and found that detailing has by far the largest impact on primary demand (long-term elasticity of .109), whereas the impact of DTC is very small (long-term elasticity of .004). Differences in the findings compared to the other studies may be partly explained by the long observation period from 1977 to 1994 that includes the launch of the category but ends before 1997 when restrictions on patient-oriented advertising were relaxed.

The cited studies are subject to several limitations that may have led to inconclusive results. First, most studies involve only one or a handful of product categories, limiting the generalizability of their findings. The study by Iizuka and Jin (2005) is an exception in this respect. The authors access data from a representative survey among physicians that covers all categories of

Table 1

Prior Research on Primary Demand Effects of Physician- and Patient-oriented Marketing

						Control of Estimation Bias		Findings on Primary Demand Effects in Terms of Elasticity		
Study	**Model**	**Level of analysis**	**Dependent variable**	**Scope of database**	**Marketing mix elements**	**Hetero-geneity**	**Endo-geneity**	**Detailing**	**Professional journal advertising**	**Direct-to-consumer advertising**
Berndt et al. (1995)	Log-log	Category	Patient days of ulcer therapy	One product category, 1977-1994	*DET*[1], *ADV*[1], *DTC*[1], *PRC*	n.a.	✓	Short-term:[2] .033 Long-term:[2] .109	.012 .039	.001 .004
Calfee, Winston, and Stempski (2002)	-[3]	Category	Unit sales (prescriptions)	One product category, 1995-2000	*DTC*, *PRC*	n.a.	par-tially[4]	-	-	N.S.
Chintagunta and Desiraju (2005)	Log-log	Category	Unit sales (standard units)	One product category across five countries, 1998-1999	*DET*, *OME*, *PRC*	n.a.	✓	.02-.09 (N.S. for three countries)	-	-
Iizuka and Jin (2005)	Log-log, Linear, Log-linear, Linear-log	Category	Patient visits	Total U.S. market, 1994-2000, Physician survey	*DTC*	Inter-cept	par-tially[4]	-	-	.014-.024[5]
Narayanan, Desiraju, and Chintagunta (2004)	Log-linear	Category	Unit sales (prescriptions)	One product category, 1993-2002	*DET*, *DTC*, *ADV*, *OME*, *PRC*	n.a.	par-tially[4]	N.S.	-	.023[6]
Rosenthal et al. (2003)	Log-log	Category	Unit sales (sold units)[7]	Five product categories, 1996-1999	*DET*, *DTC*	Inter-cept	✓	.017-.034	-	.096-.114
Wosinska (2002)	Mixed logit	Physician	Brand choice (prescriptions)	One product category, 1996-1999, (six brands)	*DET*, *DTC*, *CP*	Inter-cept, *CP*	-	> 0 (smaller than DTC)	-	> 0 (larger than detailing)
This study	Log-log	Brand	Unit sales (standard units)	86 product categories, 2000-2005 (2,831 brands)	*DET*, *DTC*, *ADV*, *PRC*	✓	✓	Short-term: .005-.107 Long-term: .030-1.08	.000-.034 .000-.381	.000-.036 .000-.261

Notes: *DET* = Expenditures on detailing, *DTC* = Expenditures on direct-to-consumer advertising, *ADV* = Expenditures on professional journal advertising, *OME* = Other marketing expenditures, e.g., physician meetings, *PRC* = Price, *CP* = Patient copayments

1. *DET* = Detailing minutes, ADV = No. of medical journal pages, *DTC* = Target rating points.
2. Elasticity estimates are only reported for stock variables in the paper. By using information on carryover and mean stock levels for the analyzed brands, we converted these figures into elasticities with respect to expenditures.
3. Exact model specification is not reported in the paper.
4. Endogeneity concerns remain because either the exogeneity assumption was tested only for a limited number of variables or relevant variables such as physician-oriented marketing are omitted.
5. Elasticity estimate based on log-log model.
6. Elasticity estimates are not reported in the paper. We thank Sridhar Narayanan for providing us with the exact figure.
7. No further information on sales units are provided in the paper.

the U.S. pharmaceutical market. Unfortunately, the authors include only DTC in their model. Results are therefore likely to be affected by variable omission bias. Second, the studies adopt category sales as the level of analysis that is highly aggregated. Especially in cases when only one product market is analyzed, the number of observations is very small and variance is low, reducing the chance to detect potential effects. An exception is Wosinska's (2002) study, which uses disaggregate data for modeling brand choice at the physician level.

To summarize, the evidence of primary demand effects with respect to patient-oriented and physician-oriented marketing is mixed. Only a small number of studies investigated physician-oriented marketing mix elements such as detailing or professional journal advertising. There remain concerns about the consistency of estimates in some cases because of omitted variables or heterogeneity issues. The major limitations of prior research, however, are its focus on selected product categories and the application of category sales models. This study aims to overcome these limitations. As Table 1 shows, we use data from 86 categories in the U.S. market. We apply a novel approach to measure primary demand effects with aggregate data at the brand level. Therefore, we can use more data and obtain more efficient estimates. Additionally, we employ estimation techniques that enable us to take advantage of cross-sectional variation as well as time variation and to control for several sources of estimation bias.

Decomposition of demand effects with aggregate data

Researchers interested in the measurement of primary demand effects with aggregate data predominantly used models that link category sales with marketing variables.[1] For example, Nijs et al. (2001) employ a vector-autoregressive modeling framework to estimate short-term as well as long-term primary demand effects of consumer price promotions across 560 consumer product categories. A similar approach was applied by Srinivasan et al. (2004). The high aggregation level, however, represents a major limitation to category sales models because information is lost in the aggregation.

Recently, van Heerde, Leeflang, and Wittink (2004) suggested an estimation framework to decompose sales promotion effects with aggregate data. Their framework builds on the idea of estimating a system of equations that reflects the impact of promotion variables on four criterion variables (e.g., own-brand sales, cross-brand sales) derived from a decomposition of unit sales. The framework allows for the analysis of marketing mix elements, such as promotions, that can be handled as a binary variable (a brand is on or off promotion in one period). However, it is not well-suited for mix elements whose intensity level is changed gradually over time (e.g., the level of detailing expenditures).

Nair, Dubé, and Chintagunta (2005) also propose a model to measure primary and secondary demand effects with aggregate data. They derive the aggregate demand system that corresponds to the individual-level choice and quantity models frequently discussed in the promotion literature (e.g., Gupta 1988). An appealing feature of their model is the direct link of aggregate demand to consumer theory. However, it is well known that structural demand models are consistently estimated only if the underlying demand process is specified correctly. In contrast, reduced-form models are more robust because they are less vulnerable to specification error (e.g., Chintagunta, Dubé, and Goh 2005). In the next section, we propose a reduced-form model to measure primary demand effects with aggregate data at the brand level.

Proposed Method for the Measurement of Primary Demand Effects

We define the primary demand effect as the incremental change in category sales that is

due to a change in a variable such as detailing expenditures. In this study, we measure the effect in terms of a relative change (primary demand elasticity). Without loss of generality, we focus on only one variable, advertising, for the development of the method.

We start with the definition that category sales are the sum of sales of all brands.[2] Hence, any change in category sales must be incorporated into brand sales. A company's own advertising expenditures and the expenditures by competitors affect sales of a brand in different ways. On the one hand, advertising may have a substitution effect, i.e., sales are gained from other brands without affecting total sales of the category. On the other hand, advertising expenditures may attract new buyers to the category or increase consumption among existing buyers. We do not consider increased consumption a relevant source of primary demand for pharmaceuticals since drug consumption is usually linked to a specific dosing regime.

From a general brand-demand function, we derive an equation that expresses growth of brand sales as a function of growth of a company's own advertising expenditures and its competitors' (details can be found in the technical appendix at http://www.msi.org/techapp/07-117):

$$\rho_{q_{it}} = \varepsilon_i \rho_{adv_{it}} + \sum_{j \neq i \in I}^{I} \varepsilon_{ji} \rho_{adv_{jt}}, \forall i, j \in \{I\}, \quad (1)$$

where $\rho_{q_{it}}$ denotes growth of brand i's sales in period t, ε_i is the brand's sales elasticity with respect to the company's own advertising, and ε_{ji} represents its sales elasticity with respect to advertising by competitor j. The terms $\rho_{adv_{it}}$ and $\rho_{adv_{jt}}$ measure the growth in advertising expenditures for the focal brand and its competitors.

Since the brand-demand function entails both primary and secondary demand effects, we can determine the primary demand effect from analyzing the brand-demand system. Equation 1 quantifies the sales gains and losses of brand i that result from changes in the company's advertising expenditures and its competitors'. This is true for all brands in a given market. If we add up the advertising-induced sales gains and losses of all brands, sales shifts that are due to competitive substitution cancel each other out. The residual sales can only be the result of the primary demand effect of advertising. Using this idea, we obtain a measure of primary demand effect that aggregates brand-level sales elasticities instead of brand sales, which is required for the application of a category sales model (details can be found in the technical appendix at http://www.msi.org/techapp/07-117):

$$\rho_{(Q,ADV)t} = \sum_{i=1}^{I} ms_{it} \left(\varepsilon_i \rho_{adv_{it}} + \sum_{j \neq i \in I}^{I} \varepsilon_{ji} \rho_{adv_{jt}} \right), \quad (2)$$

where $\rho_{(Q,ADV)t}$ measures growth of category sales due to changes in the brands' advertising expenditures and ms_{it} denotes the market share of brand i in period t.

This measure is exclusively expressed in terms of brand-level measures and can be calibrated with estimates from a brand sales model. Hence, there is no need to aggregate brand sales data, as is done in a category sales model, which would result in an unnecessary loss of information. In fact, a category sales model is likely to understate the true responsiveness of primary demand to advertising because it ignores the heterogeneity of own and cross-effects on brand sales. Under the assumption of brand heterogeneity, it follows from Equation 2 that the direction and the magnitude of primary demand effects depend on *which brands* change their expenditures in *which direction* and to *what extent*.

Illustration of primary demand dynamics

Consider the following illustrative example of a market with two brands (see Table 2). Assume that each brand sells 1,000 units and spends 50 monetary units on advertising. Own brand sales effect (in terms of elasticity) equals .10 for both brands. The cross-effect of

Table 2

Demonstration of Various Primary Demand Effect Scenarios (Illustrative Example)

	Ad Expenditures in Monetary Units				Sales in Units			
	Base period	Scenario I	Scenario II	Scenario III	Base period	Scenario I	Scenario II	Scenario III
Brand 1	50	100	50	25	1,000	1,100	900	800
Brand 2	50	50	100	125	1,000	950	1,100	1,175
Category	100	150	150	150	2,000	2,050	2,000	1,975
	Relative Change in Ad Expenditures				**Relative Change in Sales**			
	Base period	Scenario I	Scenario II	Scenario III	Base period	Scenario I	Scenario II	Scenario III
Brand 1	—	100%	0%	–50%	—	10%	–10%	–20%
Brand 2	—	0%	100%	150%	—	–5%	10%	17.5%
Category	—	50%	50%	50%	—	2.5%	0%	–1.25%
Category sales elasticity						.05	0	–.025

Sales growth equations used in the example, consistent with equations 1 and 2:

Brand 1 $\rho_{q_1} = .10\rho_{adv_1} - .10\rho_{adv_2}$

Brand 2 $\rho_{q_2} = .10\rho_{adv_2} - .05\rho_{adv_1}$

Category $\rho_{Q,ADV} = ms_1(.10\rho_{adv_1} - .10\rho_{adv_2}) + ms_2(.10\rho_{adv_2} - .05\rho_{adv_1})$.

brand 1's expenditures on brand 2's sales is –.05, whereas the cross-effect of brand 2's expenditures on brand 1's sales equals –.10. Apparently, every sales gain for brand 2 comes from brand 1. In contrast, brand 1 also benefits from market expansion.

We discuss three scenarios. In each scenario, total expenditures of the category are increased by 50% (from 100 to 150). In Scenario I, brand 1's expenditures increase by 100% (from 50 to 100), while brand 2's expenditures remain constant. From Equation 1, it follows that sales of brand 1 increase by 10% (.10 × 100% − .10 × 0% = 10%) or 100 sales units. Brand 2 loses 5% (.10 × 0% − .05 × 100% = −5%) or 50 units to brand 1. The remaining 50 units for brand 1 can only come from market expansion. Hence, market sales rise from 2,000 to 2,050 units, which represents an increase of 2.5%. By using the brand-level primary demand measure (Equation 2), we verify that the change in category sales is indeed 2.5% (.50 × .10 × 100% + .50 × .10 × 0% − .50 × .10 × 0% − .50 × .05 × 100% = 2.5%). In Scenario II, we assume that brand 2 increases its expenditures by 100%, while brand 1's expenditures stay constant. By using Equation 1, it is easy to recognize that brand 1 now loses 100 units or 10% of its sales, and brand 2 wins 100 units or 10%. Total sales of the category remain constant at 2,000 units (900 + 1,100 = 2,000), which is confirmed by the application of Equation 2: .50 × .10 × 0% + .50 × .10 × 100% − .50 × .10 × 100% − .50 × .05 × 0% = 0%.

In Scenario III, we assume that brand 1 decreases its expenditures by 25 monetary units (–50%), and brand 2 increases its expenditures by 75 units (+150%). Applying Equation 1, we obtain a sales decrease of 200 units or −20% for brand 1 [.10 × (–50%) − .10 × 150% = −20%] and a sales increase of 175 units or 17.5% for brand 2 [.10 × 150% − .05 × (–50%) = 17.5%]. As a result, category sales shrink by 25 units or −1.25%, which can also be obtained from Equation 2.

Limitations of the category sales model

The illustrative example provides important insights into the dynamics of primary demand.

Recall that category expenditures were increased by the same amount from 100 to 150 or 50% in all three scenarios. The associated effects on primary demand, however, are quite different. Category sales increased in Scenario I, remained constant in Scenario II, and decreased in Scenario III (see Table 2). By computing the category sales elasticity with respect to category advertising, we obtain very different, even counterintuitive, yet explainable results. Elasticity is .05 in Scenario I, it is 0 in Scenario II, and it turns negative, −.025, in Scenario III. From Scenario II, we would falsely conclude that primary demand does not react to advertising in this market. However, from Scenario I, we know that this is not true. Scenario III even suggests that category sales shrink if total advertising expenditures rise, which is counter to intuition.

The differences in the cross-effects of the two brands explain these discrepancies in primary demand effects. In our example, only brand 1 is able to change primary demand by attracting or losing customers. In contrast, the effect of brand 2's advertising expenditures is entirely substitutive. As a consequence, we notice an increase in primary demand when brand 1 increases its advertising expenditures (Scenario I), a decrease when it decreases its expenditures (Scenario III), and we observe no effect on primary demand when its expenditure level does not change (Scenario II). By aggregating brand sales data, a category sales model loses important information on brand heterogeneity. It implicitly assumes that the increase in total advertising expenditures by *x*% always has the same effect on category sales. This assumption holds only if own and competitive brand sales effects are homogenous, but not if brand heterogeneity is present. Since all three scenario types are likely to occur in an empirical dataset, i.e., we may observe periods with negative, positive, and zero effects, a category sales model tends to *understate* the true *primary demand responsiveness*. This may explain why many previous studies found only very small or even insignificant primary demand elasticities.

In addition to this attenuation effect, we expect that *estimation efficiency* is *higher* for the proposed brand-level model because of a larger sample size and a higher variation in the focal variables. Consider, for example, the common situation where data are only available for one product market over a limited time. It may well turn out that the number of periods is not sufficient to obtain stable estimates by a category sales model. Pooling brand-level data to estimate a brand sales model may create a large enough sample size instead. Note that the efficiency advantage of the brand-level model also holds in markets with homogenous brand sales effects when the category sales model does not suffer from the attenuation effect.[3]

Proposed measure of primary demand responsiveness

The discussion of primary demand dynamics above shows that estimates of primary demand responsiveness obtained by a category sales model lack a clear interpretation in heterogeneous markets. The illustrative example revealed that dividing the relative change in category sales that is due to *individual* brand advertising expenditures by the relative change in *total* advertising expenditures in the category does not yield a meaningful measure of primary demand responsiveness. The sign and magnitude of the implied primary demand elasticity depends not only on the estimated brand sales effects but also on the selection of brands that vary their expenditures. In order to obtain a meaningful measure of primary demand responsiveness, we need to remove the effects that arise from differences in competitive expenditure dynamics across brands. For this purpose, we set $\rho_{adv_{it}} = \rho_{adv_{jt}}, \forall i, j$, which implies $\rho_{ADV_t} = \rho_{adv_{it}} = \rho_{adv_{jt}}$. By dividing Equation 2 by ρ_{ADV_t}, we obtain our final proposed measure of inherent primary demand responsiveness:

$$\varepsilon_{(Q,ADV)_t} = \sum_{i=1}^{I} ms_{it}(\varepsilon_{i\cdot} + \sum_{j \neq i \in I}^{I} \varepsilon_{ji}), \qquad (3)$$

where $\varepsilon_{(Q,ADV)_t} = \rho_{(Q,ADV)_t}/\rho_{ADV_t}$, which can also be interpreted as an innate primary-demand

elasticity. Note that we do not need to observe equal expenditure growth rates empirically but use them in a *conceptual sense* to define our measure. By setting the advertising expenditure growth rates of all competitors to be equal, we vary total advertising expenditures in the category without changing the status quo of competition. As a result, the measure of primary demand responsiveness is not confounded by the effects of competitive dynamics and allows for a meaningful comparison of marketing mix elements with respect to their potential to drive primary demand. In the empirical application, we use this expression to determine which marketing element is most effective in driving primary demand for prescription drugs in the United States.

Empirical Model Specification and Estimation

In this section, we specify the brand sales model that we use to describe the demand for prescription drugs in the United States during the period 2001 through 2005. We provide details on model estimation at http://www.msi.org/techapp/07-117.

Brand sales model

Let sales of brand i in category k and period t be defined as follows:

$$\begin{aligned}\ln q_{kit} = {} & \alpha_{0ki} + \alpha_{1ki}\ln det_{kit} + \alpha_{2ki}\ln adv_{kit} \\ & + \alpha_{3ki}\ln dtc_{kit} + \alpha_{4ki}\ln prc_{kit} \\ & + \sum_{j=1,j\neq i}^{2}(\beta_{1kji}\ln det_{kjt} + \beta_{2kji}\ln adv_{kjt} \\ & + \beta_{3kji}\ln dtc_{kjt}) + \beta_{4ki}\ln comdet_{kit} \\ & + \beta_{5ki}\ln comadv_{kit} + \beta_{6ki}\ln comdtc_{kit} \\ & + \beta_{7ki}\ln cinno\_prc_{kit} + \beta_{8ki}\ln cgen\_prc_{kit} \\ & + \gamma_{1ki}LCT_{kit} + \gamma_{2ki}\ln L_{kit} \\ & + D\_Ind_{kit}\ln\gamma_{3ki} + D\_Loss_{kit}\ln\gamma_{4ki} \\ & + \delta_{ki}\ln q_{kit-1} + \sum_{s=1}^{S-1}D\_Qual_{ski}\ln\varphi_{s} \\ & + \varphi_{5}\ln OE_{ki} + D\_Radic_{kt}\ln\varphi_{6} \\ & + \sum_{h=1}^{H-1}SD_{hkt}\ln\varphi_{6+h} \\ & + \sum_{k=1}^{K-1}D\_Cat_{k}\ln\varphi_{10+k} + u_{kit}, \\ & \text{with } u_{kit} \sim N(0,\sigma_{ki}^2) \end{aligned} \quad (4)$$

where

q_{kit}: Unit sales of brand i in category k and period t

det_{kit}: Expenditures on detailing by brand i in category k and period t

adv_{kit}: Expenditures on professional journal advertising by brand i in category k and period t

dtc_{kit}: Expenditures on DTC by brand i in category k and period t

prc_{kit}: Unit price of brand i in category k and period t

$comdet_{kit}$: Cumulative expenditures on detailing by brand i's competitors excluding first and second entrant in category k and period t

$comadv_{kit}$: Cumulative expenditures on professional journal advertising by brand i's competitors excluding first and second entrant in category k and period t

$comdtc_{kit}$: Cumulative expenditures on DTC by brand i's competitors excluding first and second entrant in category k and period t

$cinno\_prc_{kit}$: Average price of brand i's competitive innovative drugs in category k and period t

$cgen\_prc_{kit}$: Average price of brand i's competitive generic/me-too drugs in category k and period t

LCT_{kit}: Elapsed time since launch of brand i in category k and period t

D_Ind_{kit}: Approval of an additional indication for brand i in category k and period t (0/1)

D_Loss_{kit}: Loss of patent status by (innovative) brand i in category k and period t (0/1)

D_Qual_{ski}: Categories of innovativeness s of brand i in category k (0 = generic/me-too drug, 1 = incremental innovation, 2 = market

breakthrough, 3=technological breakthrough, 4 = radical innovation)

OE_{ki}: Order of entry of brand i in category k

D_Radic_{kt}: Availability of a radical innovation introduced after 2000 in category k and period t (0/1)

SD_{hkt}: Seasonal dummy variable for quarter h in category k and period t

D_Cat_k: Category dummy variable for category k

$\alpha, \beta, \gamma, \delta, \varphi$: (Unobserved) parameter vectors

u_{kit}, σ^2_{ki}: Error term and brand-specific error variance

k= 1, 2, . . . , K (number of categories)

i= 1, 2, . . . , j, . . . , I_k (number of brands per category)

t= 1, 2, . . . , T_i (number of periods per brand)

s= 1, 2, . . . , S (number of innovativeness classes)

h= 1, 2, . . . , H (four quarters).

The α-parameters measure the effects of a company's marketing mix elements, whereas the β-parameters represent the cross-effects of competitors' marketing activities. For each communication mix element, we estimate three cross-effects. Two cross-effects capture the impact of competitive marketing expenditures of the first and second entrant in the category. Previous research has shown that early entrants often achieve a dominant market position. Their marketing instruments are more effective compared to later entrants (e.g., Bowman and Gatignon 1996), and they exert a strong influence on the formation of a buyer's category preferences (Carpenter and Nakamoto 1989). The expenditures of the remaining competitors are cumulated to measure their combined impact on the company's brand sales. For the price instrument, we acknowledge that demand for a prescription drug is usually inelastic, unless generic competitors have entered the market. We therefore include two separate competitive price variables: the average price of competitive innovative brands and the average price of competitive generic/me-too brands. We explain how we classify the brands in our sample into these groups in the data section. We could have specified an even larger number of cross-effects, at most, a cross-effect for each individual competitor by category. However, this would considerably increase the number of parameters to be estimated and likely result in an overspecified or unidentified model. Nonetheless, the inclusion of 11 competitor variables paired with the estimation of *brand-specific* cross-effects enables us to capture the richness of asymmetric competitive relations among brands at sufficient depth.

In addition to the marketing mix effects, the brand sales model incorporates a number of other important variables that have been shown to impact sales of pharmaceuticals. We account for differences in drug innovativeness by adopting the measure of Sorescu, Chandy, and Prabhu (2003). We include the elapsed time and the log of elapsed time since launch of the brand to control for brand life-cycle effects (Brockhoff 1967). The model also accounts for order-of-entry effects (Urban et al. 1986). We further control for the addition of a new indication of a brand, i.e., drug use is allowed for another disease, which should broaden its sales basis (e.g., Berndt et al. 1995). A significant loss in sales can be expected if an innovative brand loses its patent protection. We account for this effect in the model. Finally, the introduction of a radical innovation may expand the category and thus increase sales of incumbent brands (van Heerde, Mela, and Manchanda 2004).

In many countries, distribution is less an issue in pharmaceutical markets because pharmacies are required to list every drug. In the United States, however, distribution may be relevant due to the existence of drug formularies issued by health insurers. Given our observation period of five years, the effect should be rather

fixed over time. By specifying a heterogeneous brand constant (α_{0ki}), we explicitly account for such effects. This specification enables us also to control for the influence of other unobserved time-fixed variables such as management luck or brand equity (e.g., Berndt et al. 1995; Fischer, Shankar, and Clement 2005).

Equation 4 pools brands from various categories that are likely to differ in terms of market size. We account for market size differences by estimating category-specific fixed effects. In appendices available at http://www.msi.org/techapp/07-117 we explain how these parameters and the brand-specific constants are identified. We capture marketing dynamics in the model by including lagged sales. Since we do not assume serially correlated errors, our model formulation is consistent with the partial adjustment model.[4] Finally, we account for seasonal variation in demand by including dummy variables that represent one of the four quarters of the year.

Data

IMS Health, Inc. provided us access to its MIDAS database, which covers marketing, sales, and other product information for all prescription drug categories in the United States. From this database, we identified 86 categories in which firms have spent money on DTC campaigns since the abolition of the DTC advertising ban in 1997. We obtained marketing and sales data on all brands marketed in these categories for a period of 21 quarters from quarter 4, 2000, until quarter 4, 2005. The dataset encompasses 12,007 brands, which represent approximately 85% of total U.S. prescription drug sales. Many brands, however, have only very limited economic importance. We reduced the dataset by excluding brands if their average market share did not exceed 1% and if they had no marketing expenditures. As a result, we were left with 2,831 brands, which cover, on average, 94% of total category sales.

The IMS-MIDAS database offers information on expenditures on detailing, professional journal advertising, DTC, revenues (all in U.S.$), and sales counted in standard units. In addition, we have knowledge of the product launch date, which enables us to obtain order-of-entry and life-cycle information. We computed prices from revenues and unit sales. In addition, we collected data on the approval process of the brands in our dataset, which are publicly available on the website of the Food and Drug Administration (http://www.fda.gov). The FDA classifies drugs as priority review drugs (therapeutic advance over available therapy) or standard review drugs (therapeutic qualities similar to those of an already marketed drug). The files also provide information on whether the drug represents a new molecular entity or not. Following Sorescu, Chandy, and Prabhu (2003), we use this information to classify innovative drugs into four categories of drug innovativeness (category names for the variable *D_Qual* are provided in the variable list below Equation 4).[5] All drugs that do not fall in one of these categories are classified as generic or me-too drugs. In addition, we know when a firm got approval for a new indication for its drug and when a drug lost or will lose its patent protection. From these data, we constructed the time-varying dummy variables: *D_Loss* and *D_Ind*. *D_Loss* takes the value 1 in all periods after an innovative brand has lost its patent protection status. *D_Ind* takes the value 1 in all periods after the FDA has approved a new indication for the brand. Finally, the dummy variable *D_Radic*, which measures the introduction of a radical innovation at the category level, takes the value 1 in all periods and for all brands of a category after the focal category has witnessed the introduction of a radical innovation.

The unique strength of this database is derived from the complete market coverage and completeness in relevant variables. We therefore have much confidence in the generalizability of our results with respect to prescription drugs. In addition, we are able to separate short-term from long-term marketing effects.

Table 3
Descriptive Statistics (2,831 Brands)

Variable	Mean	Standard Deviation	Sources of Variation (std. dev. relative to unit sales)			
			Categories		Brands	
			within groups	across groups	within groups	across groups
Units sales in million standard units	18.95	60.44				
Revenues in U.S.$ million	14.96	65.94				
Market share in standard units	2.9%	7.3%				
Detailing expenditures in. U.S.$ million	.41	1.73	.6%	8.6%	1.1%	11.5%
Professional journal advertising expenditures in U.S.$ million	.04	.24	.1%	.9%	.2%	1.4%
DTC expenditures in U.S$ million	.26	2.10	1.3%	6.6%	2.5%	13.4%
Price in U.S.$ per standard unit[1]	8.70	51.22	.0%	.0%	.0%	.4%
Elapsed time since launch in years	11.51	9.76				
Proportion of ...						
Generic/me-too drugs	76.8%					
Market breakthroughs	1.3%					
Technological breakthroughs	8.9%					
Radical innovations	5.4%					
Incremental innovations	7.6%					
Order of entry[2]	17					
Number of brands per category	34.9					
Proportion of innovative drugs with patent protection in 2001-2005	69.9%					
Proportion of drugs with approval of additional indication in 2001-2005	.4%					
Proportion of categories with introduction of a radical innovation in 2001-2005	8.1%					

Notes: All units and dollar figures are on a quarterly basis. The decomposition of variance in columns 4-7 refers to total marketing expenditures and average price at the category level and own marketing expenditures and own price at the brand level.
1. Statistic refers to the *unweighted average* price per brand. The unweighted median price is U.S. $52 per standard unit and the weighted average price amounts to US$1.46 per standard unit.
2. Median instead of mean reported.

Table 3 shows mean values and standard deviations for the variables used in the estimation. It is evident that the brands spent the majority of their marketing resources on detailing activities. DTC is second, followed by journal advertising, underlining the importance of DTC as a new tool of pharmaceutical marketing. Note that the mean price represents an unweighted arithmetic mean across brands. It is approximately U.S. $1.46 per standard unit, if prices are weighted by unit sales. All marketing variables show a considerable variation relative to their means. We notice that a significant amount of variance is lost if data are aggregated to the category level (compare the last four columns of Table 3).

Table 4
Parameter Estimates of Brand Sales Model (2,831 Brands)

	Parameter Estimate	Estimated Std. Dev. of Parameter Distribution
Constant	4.32 (.042)	1.50 (.024)
Lagged own brand sales	.712 (.004)	.105 (.003)
Company's marketing mix		
Detailing	.061 (.001)	.046 (.001)
Professional journal advertising	.027 (.001)	.019 (.001)
DTC	.039 (.001)	.022 (.001)
Price	–.215 (.003)	.090 (.003)
Competitors' marketing mix		
Detailing (first entrant)	.011 (.001)	.015 (.001)
Detailing (second entrant)	–.010 (.001)	.002 (.001) *NS*
Detailing (all other entrants)	–.002 (.002) *NS*	.015 (.001)
Professional journal advertising (first entrant)	.013 (.002)	.012 (.002)
Professional journal advertising (second entrant)	–.017 (.002)	.009 (.002)
Professional journal advertising (all other entrants)	.006 (.001)	.001 (.001) *NS*
DTC (first entrant)	–.003 (.004) *NS*	.007 (.004) *NS*
DTC (second entrant)	–.011 (.003)	.008 (.004)
DTC (all other entrants)	.005 (.001)	.004 (.001)
Price (innovative drugs)	–.095 (.006)	.041 (.003)
Price (generic/me-too drugs)	.021 (.004)	.032 (.002)
Innovativeness (reference group = generic/me-too drugs)		
Incremental innovation (0/1)	.192 (.009)	
Market breakthrough (0/1)	.428 (.017)	
Technological breakthrough (0/1)	–.057 (.009)	
Radical innovation (0/1)	.586 (.010)	
Covariates		
Elapsed time since launch: parameter γ_1	–.006 (.001)	.009 (.001)
Elapsed time since launch: parameter γ_2	.088 (.008)	.053 (.008)
Order of entry	–.094 (.007)	
New drug indication(s) (0/1)	1.07 (.040)	1.61 (.034)
Loss of patent protection (0/1)	–.474 (.015)	.665 (.016)
Introduction of a radical innovation (0/1)	.041 (.016)	
Log likelihood = –20,956.80/ Sample size = 47,308/ R^2 = .973		

Notes: Standard errors in parentheses; *NS* = Not significant ($p > .05$; two-sided *t*-test); Parameter estimates for seasonal dummies and product category dummies are not shown but available from the authors upon request.

Table 3 reveals that the majority of brands are generic or me-too brands, respectively. Almost 25% are, however, innovative brands, and 70% were still under patent protection at the end of 2005. Very few drugs obtained approval for an additional indication in the five-year observation period. Of the 86 categories, 8% experienced the introduction of a radical innovation from 2001 through 2005.

Results

Estimation results for the brand sales model are shown in Table 4. Details on model estimation are given at http://www.msi.org/techapp/07-117. The model provides an excellent in-sample fit to the data. R^2 amounts to .973, even though the sample size is very large, with 47,308 observations. The excellent fit is due to several factors. Our model captures many relevant variables. A simple OLS regression that does not account for brand and category heterogeneity (2,831 brands and 86 categories) produces an R^2 of .564! The remaining variance can be explained by accounting for differences in market size, in the base level of brand sales, and in marketing responsiveness parameters.

Marketing mix elasticities

Although we use quarterly data, we recognize that some estimates may still suffer from temporal aggregation bias. Table 5 summarizes short-term marketing-mix elasticities that are corrected for a temporal aggregation bias and their implied long-term effects (for technical details, see http://www.msi.org/techapp/07-117).

A company's estimated short-term marketing mix effects are relatively small. Table 5 demonstrates that the short-term effect of its detailing expenditures is largest at .061, followed by DTC at .014, and professional journal advertising at .010 (all significant at $p <$ .01). These figures represent mean values of marketing responsiveness. We find consider-

Table 5
Estimated Mean Marketing Mix Parameters Corrected for Temporal Aggregation Bias

	Estimated Short-term Effect	Estimated Long-term Effect
Company's marketing mix		
Detailing	.061 (.001)	.210 (.005)
Professional journal advertising	.010 (.000)	.035 (.005)
DTC	.014 (.000)	.050 (.005)
Price	–.215 (.012)	–.747 (.013)
Competitors' marketing mix		
Detailing (first entrant)	.011 (.001)	.038 (.005)
Detailing (second entrant)	–.010 (.001)	–.035 (.005)
Detailing (all other entrants)	–.002 (.002) *NS*	–.007 (.007) *NS*
Professional journal advertising (first entrant)	.005 (.001)	.017 (.008)
Professional journal advertising (second entrant)	–.006 (.001)	–.022 (.008)
Professional journal advertising (all other entrants)	.002 (.000)	.007 (.005) *NS*
DTC (first entrant)	–.001 (.001) *NS*	–.004 (.013) *NS*
DTC (second entrant)	–.004 (.001)	–.014 (.010) *NS*
DTC (all other entrants)	.002 (.000)	.006 (.002)
Price (innovative drugs)	–.095 (.006)	–.330 (.020)
Price (generic/me-too drugs)	.021 (.002)	.072 (.015)

Notes: Standard errors in parentheses; *NS* = Not significant ($p > .05$; two-sided *t*-test). For technical details on temporal bias correction, see the technical appendix (http://www.msi.org/techapp/07-117).

able variation of these effects across brands as is reflected by the estimated standard deviation of the parameter distribution (see the last column of Table 4). The estimated mean carryover coefficient is quite large at .712 ($p < .01$; Table 4). Given the fact that physicians are rather reluctant to change a brand if it has been found to work for a patient, the magnitude is not surprising and is comparable to previous findings for this industry. The implied long-term effects of a company's marketing expenditures are on average 3.5 times larger than their short-term effects [1/(1 – .712)]. For a company's detailing, we obtain a long-term sales elasticity of .210 ($p < .01$; Table 5). For a company's professional journal advertising and DTC, the effects are .035 and .050, respectively (both $p < .01$; Table 5). These estimates are well within the range of values reported in previous studies on pharmaceuticals (e.g., Manchanda and Honka 2005; Narayanan, Desiraju, and Chintagunta 2004; Wittink 2002).

The cross-effects of competitive marketing expenditures are generally smaller in absolute terms. These effects again vary considerably across brands (see again Table 4). Recall that competitive marketing activities may substitute a company's sales and/or expand category sales. We find both negative and positive coefficients indicating that for some brands and communication elements, the competitive-substitution effect is larger than the market-expanding effect, while the opposite is true for others. For detailing and DTC, we find the majority of individual cross-effects to be negative, which suggests stronger secondary-demand effects for these elements. For professional journal advertising, in contrast, the market-expansion effect turns out to dominate, as the majority of cross-effects are positive.

Consistent with prior research (e.g., Berndt et al. 1995; Chintagunta and Desiraju 2005), price has a significant but inelastic, average short-term impact on sales that amounts to –.215 ($p < .01$). As expected, we find the vast majority of cross-effects with respect to generic/me-too brands to be positive. Depending on the category and the brand, these effects can be quite large, pointing to the existence of severe generic competition. The cross-effects with respect to innovative drugs are, on average, negative and corroborate industry beliefs that there is only little or no price competition among innovative pharmaceutical brands (Ellison et al. 1997).[6]

Effects of control variables

Table 4 shows that we find significant (average) effects for our control variables. The

Table 6
Estimated Primary Demand Responsiveness (86 Categories)

	Mean	Median	Standard Deviation	Minimum	Maximum	No. of Categories with $\mu/SD>2$[1)]
Short-term effects						
Detailing	.052 (.002)	.053	.018	.005	.107	69 (80%)
Professional journal advertising	.009 (.001)	.009	.006	.000[2]	.034	64 (74%)
DTC	.010 (.001)	.010	.007	.000[2]	.036	63 (73%)
Price	–.301 (.003)	–.301	.030	–.384	–.240	86 (100%)
Long-term effects						
Detailing	.278 (.017)	.236	.161	.030	1.08	45 (52%)
Professional journal advertising	.109 (.009)	.091	.082	.000[2]	.381	43 (50%)
DTC	.082 (.007)	.074	.065	.000[2]	.261	40 (47%)
Price	–1.25 (.051)	–1.14	.469	–3.91	–.698	63 (73%)

Notes: Standard error of mean in parentheses. All estimated means are significantly different from zero at $p < .01$ (two-sided *t*-test). Estimates are based on estimates from brand sales model with temporal bias correction when applicable.
1. A posterior mean μ that is greater than twice its posterior standard deviation *SD* indicates a primary demand effect that is significantly different from zero.
2. We set the few negative estimates to zero since a negative elasticity is not meaningful and presumably the result of estimation error. All negative primary demand effect estimates have $\mu/SD < 2$ justifying our decision.

degree of innovativeness of a drug affects its sales relative to the sales of a me-too/generic drug. The impact is highest for radical innovations, followed by drugs that are classified as market breakthroughs and incremental innovations. To our surprise, we find a negative, albeit very small, effect for technological breakthroughs (a new chemical entity but no therapeutic advance over available therapy). Given that we control for marketing expenditures, brand equity, and other effects, a purely technological improvement—i.e., changing the chemical structure but not the therapeutic principle—which is not commanded by the market, may not be sufficient to expect a higher sales level. Consistent with previous research (e.g., Berndt et al. 1995), we find a disadvantage for later entrants. The significant parameters associated with the elapsed time since launch (γ_1) and its logarithm (γ_2) point to the existence of brand life-cycle effects. Based on the estimates, the average brand achieves its peak sales after 15 years ($-\hat{\gamma}_2/\hat{\gamma}_1$). Consistent with Berndt et al. (1995), we find a strong sales boost that follows the approval for a new indication of a drug. The expiry of the patent, in contrast, leads to a substantial loss in sales, as expected. Finally, we find that incumbent brands benefit from the launch of a radical innovation, albeit the synergetic sales effect is rather small.

Primary demand responsiveness

Estimation of the brand sales model (Equation 4) provides us with a set of posterior means and standard deviations of brand-specific sales elasticities. By using observed brand market shares in period *t*, we compute the primary demand responsiveness in that period according to Equation 3. Since we need to exclude one brand per category for estimation due to the sum constraint of category sales, we rescale the market shares of included brands so that they sum to 100%.

Table 6 displays the summary statistics for the estimated 688 measures of primary demand responsiveness (2 temporal effect types × 4 mix elements × 86 categories). We find a mean short-term responsiveness for detailing that corresponds to .052. The mean short-term responsiveness for professional journal

advertising and DTC is substantially smaller and amounts to only .009 and .010, respectively. In addition, approximately one-quarter of categories with respect to professional journal advertising and DTC have posterior means that are greater than twice its posterior standard deviation (see the last column of Table 6).[7] Consistent with Allenby, Arora, and Ginter (1998), we interpret this ratio as a threshold to classify a primary demand effect as being significantly different from zero. The short-term primary demand responsiveness of price amounts to −.301.

Long-term primary demand responsiveness is considerably higher than short-term responsiveness, reflecting the strong carryover effect that is typical for prescription drugs. The mean long-term effect of detailing totals .278. Note, however, that this value is driven to a certain extent by a few categories carrying very high values. The median is .236. The long-term primary demand responsiveness for professional journal advertising is considerably lower, with a mean value of .105. We find an even lower mean value of .082 for DTC. Primary demand is price elastic in the long run with a mean value of −1.25, although it does not reach the magnitude of price elasticities frequently observed for consumer products.

Overall, the results provide interesting insights into the role of pharmaceutical marketing as a driver of primary demand. We can now answer the question of whether patient-oriented or physician-oriented marketing activities have a stronger influence on category sales. From the analysis of 86 categories, it is obvious that detailing is, on average, the most potent driver of primary demand among the three communication mix elements. Moreover, it turns out that primary demand is least responsive to DTC. This conclusion does not alter if we consider the median instead of the mean.

So far, we considered average effects across the 86 categories. The standard deviations and the ranges of values reported in Table 6 emphasize that we find considerable variation in primary demand responsiveness for all four marketing mix elements. We also observe an evolution of primary demand responsiveness in several categories. In the next section, we analyze several moderator variables to better understand the factors that drive primary demand responsiveness of marketing mix elements over time and categories.

Moderator Analysis

We base the selection of moderators on prior marketing theory and research (Nijs et al. 2001; Sethuraman and Tellis 1991; Srinivasan et al. 2004), although we must affirm that previous research has focused on price promotions but not advertising and salesforce. Specifically, we consider three groups of variables: (1) *marketing characteristics*—the level of marketing expenditures, the introduction of major new products, and the price level; (2) *product characteristics*—the emphasis of a category on chronic care versus acute care, the age of the category, and whether or not it focuses on life-threatening diseases; and (3) *market characteristics*—the size of the category and the degree of market concentration. Additionally, we include a trend variable. Thus, we have nine variables that may drive primary demand responsiveness to four marketing elements, resulting in 36 moderating effects to be estimated. Given that prior research focused on promotional performance in consumer goods categories and the fairly large number of moderating effects, our second-stage analysis is mostly explorative in nature.

We estimate four linear models that use estimated long-term primary demand responsiveness of detailing, professional journal advertising, DTC, and price as dependent variables. Our focus is on long-term effects, since managers and policymakers are mostly interested in total effects of their decisions. Econometrically, we use Generalized Least Squares estimation because we decompose the error variance into a category-specific part that

controls for unobserved fixed effects and an idiosyncratic component that is serially correlated and heteroscedastic. With this error term specification, we account for the fact that the dependent variable results from estimation and is therefore subject to measurement error.

The level of marketing expenditures is defined as the average expenditure level in U.S.$ millions over the observation period per category. For the detailing, professional journal advertising, and DTC equations, we consider the expenditures on the corresponding element. For the price equation, we include the total expenditures across all three elements. We take the log of expenditures to account for diminishing returns. Following Nijs et al. (2001), a newly launched brand that was able to capture an average market share of more than 5% over its observed life cycle was classified as a major new product introduction. The price level is operationalized as the average category price. A knowledgeable pharmacist classified the 86 categories into categories that are focused on chronic care versus acute care and life-threatening versus nonlife-threatening diseases. We measure the age of a category by the time elapsed since launch of the pioneer brand. Market size is determined by the average number of standard units sold during the observation period. Here again, we take the log of standard units to account for diminishing returns. Market concentration is measured by the Herfindahl-Index (see also Srinivasan et al. 2004). Time trend represents the calendar quarters of our observation period. Time trend, market concentration, age of category, price level, and number of major new-product introductions are time-varying variables.

Table 7 presents the findings of our second-stage analysis. Overall, we find many significant effects underlining the explanatory power of the chosen moderators.

Marketing characteristics

Depending on the type of market response, the impact of marketing expenditures on sales responsiveness can be positive or negative. Previous research on price-promotion elasticities (Nijs et al. 2001; Srinivasan et al. 2004) found that promotional frequency increases price-promotion elasticities, whereas promotional depth has a decreasing influence. Evidence on communication mix elasticities is not available from these studies. Based on the findings from pharmaceutical ROI analyses (Neslin 2001; Wittink 2002), we expect a positive impact of the level of physician-oriented marketing expenditures, but a negative correlation between the level of DTC expenditures and DTC primary demand responsiveness in our sample. These studies show that ROI for DTC is small or even negative, while it is large for detailing and professional journal advertising. Hence, firms seem to overspend on DTC. Indeed, we find a significant negative effect for the level of expenditures for DTC ($p < .01$), but positive significant effects for detailing ($p < .01$) and professional journal advertising ($p < .10$).

Nijs et al. (2001) argue that price-promotion effectiveness should be lower in categories with major new-product introductions, which is supported by their empirical results. Our analysis confirms this finding with respect to professional journal advertising and DTC. However, one may also argue that major new product introductions increase primary demand responsiveness because they raise the awareness of physicians for that category. Consistent with this argument, we find a positive association with detailing.

Finally, we expect the impact of the price level on the responsiveness of marketing expenditures to be negative. In view of sharply rising health care costs, physicians and patients have increased incentives for lower drug therapy costs. Hence, they should be less open to marketing campaigns that promote drugs in expensive categories. Our results are in line with this argument.

Product characteristics

We argue that primary demand effects should be higher in categories that are focused on

Table 7

Estimated Moderating Effects of Primary Demand Responsiveness (86 Categories/effective sample size = 1,634)

	Dependent Variable: Primary demand responsiveness to ...							
	Detailing		Professional journal advertising		DTC		Price	
Constant	.868	(.135)***	.610	(.062)***	.468	(.064)***	.039	(.421)
Time trend	.001	(.001)	.001	(.000)	4.2×10^{-4}	(4.0×10^{-4})	.005	(.003)*
Marketing characteristics								
Log (average marketing expenditures in U.S.$ million)[1]	.078	(.024)***	.016	(.008)*	–.013	(.004)***	–.149	(.072)**
No. of major new product introductions in 2001-2005	.111	(.041)***	–.030	(.017)*	–.053	(.017)***	–.765	(.130)***
Price level	–.001	(.001)	–.001	(.000)**	–.001	(.000)**	–.002	(.002)
Product characteristics								
Chronic care	.107	(.066)	.063	(.025)**	.021	(.026)	–.251	(.174)
Life-threatening disease	–.491	(.061)***	–.102	(.021)***	–.005	(.021)	.784	(.167)***
Age of category	–.013	(.004)***	–.005	(.001)***	–.002	(.001)	–.004	(.010)
Market characteristics								
Log (average market size in million standard units)	.012	(.021)	–.033	(.008)***	–.075	(.007)***	–.264	(.061)***
Market concentration	–.151	(.035)***	–.145	(.016)***	–.121	(.013)***	–.068	(.080)
Error components in terms of standard deviation								
Within categories[2]	.097		.060		.038		.186	
Between categories	.155		.066		.073		.438	
R^2 (OLS based)	.140		.406		.442		.176	

Notes: Standard errors in parentheses; *** $p < .01$; ** $p < .05$, * $p < .10$ (two-sided *t*-test)

1. Includes expenditures on the respective mix element (detailing, professional journal advertising, or DTC) and total marketing expenditures for price.

2. Based on average heteroscedastic (category-specific) error variance.

chronic care but lower in categories that deal with life-threatening diseases and in older categories. Patients with a chronic disease such as hypertension or diabetes see their doctors more often and over a longer time period. For many physicians, these patients generate the largest share of income. Physicians therefore pay more attention to marketing activities in these categories and are more inclined to react to campaigns, especially if they help diagnose new patients. As a result, primary demand responsiveness should be higher in chronic care categories compared to acute care categories.

Primary demand responsiveness should be lower in categories that focus on life-threatening diseases. Here, physicians are intrinsically more motivated to stay up to date with advancements in drug therapy. As a consequence, the incremental value of information provided by commercial communication activities is lower and reduces expenditure responsiveness. We expect a lower primary demand responsiveness in older categories since these categories are in a later stage of their life cycle, when physicians and patients have had considerable experience with the product and

informative advertising has lost its relevance (Sethuraman and Tellis 1991).

As Table 7 shows, the pattern of moderating effects with respect to product characteristics is consistent across the demand effects, albeit not all estimates reach statistical significance ($p < .05$). We find a higher responsiveness in chronic care categories and a lower responsiveness in older categories and in categories with life-threatening diseases. Note that (absolute) price responsiveness is also considerably lower for drugs treating life-threatening diseases, which is absolutely consistent with our expectation.

Market characteristics

Consistent with economic theory and previous research (Nijs et al. 2001; Srinivasan et al. 2004), higher market concentration should reduce marketing effectiveness. We expect a different moderating role of the size of market for detailing, compared to professional journal advertising and DTC. Larger markets should have higher primary demand responsiveness for detailing, but lower responsiveness for DTC and professional journal advertising for the following reasons: Smaller markets represent indications whose incidence is lower in the population than for larger markets. Usually, only a small group of specialist physicians deals with such indications. Specialists are often better informed about diseases and alternative therapies than general practitioners. Thus, the perceived amount of new information provided by detailing activities is likely to be lower for physicians in these markets, reducing the efficacy of detailing expenditures. In addition, the untapped potential of physicians is higher for general practitioners than for specialists.

While a sales call ensures that the recipient actively perceives and processes the firm's message, advertising activities that target an anonymous physician and patient population must first create awareness for the message. Apparently, marketing resources are spread across many different media and formats in large categories so that they can reach a large share of the population but at the cost of lower frequency. In smaller categories, the same amount of money is spent on fewer media and formats to target the niche population, which helps establish the repetition effect of advertising. Thus, primary demand responsiveness to advertising should be larger in small categories.

The results support our arguments. We find a significant negative influence of market concentration across all three communication mix elements ($p < .01$). Hence, marketing responsiveness is larger in more competitive markets. We also find support for our argument that smaller categories enjoy higher advertising primary demand responsiveness. The coefficients for professional journal advertising and DTC are highly significant ($p < .01$). However, we find only directional support for the expected positive relationship between detailing primary demand responsiveness and the size of the market. Finally, we note that there seems to be no evidence that primary demand responsiveness is evolving over time ($p > .10$).

Conclusions

In this paper, we suggest a new method for measuring primary demand effects with aggregate data at the brand level. We show that the traditional approach of estimating a category sales model tends to understate primary demand responsiveness when heterogeneous brand sales effects are present. The proposed method overcomes this limitation. Additionally, it provides more efficient results because the sample size and sample variation are increased. We applied the method to a dataset covering 86 categories of the U.S. pharmaceutical market. This broad dataset enabled us to derive generalizable conclusions about the responsiveness of patient- and physician-oriented marketing efforts with respect to primary demand. Our findings have important implications for brand managers and society.

Implications for pharmaceutical brand managers

By studying our results and the suggested model, pharmaceutical marketing managers can better understand which marketing elements help expand the market instead of substituting sales from competitors. Such marketing elements may be particularly attractive to some marketing managers because they can increase their company's sales without hurting competitors' sales. In addition, the company's sales may benefit from competitive activities. We find that detailing is most useful in this respect. In contrast, patient-oriented marketing like DTC shows negligible effects on primary demand. However, it appears to be a quite effective element for stealing sales from competitive brands. If competitors retaliate effectively by increasing their DTC expenditures, the net sales effect could be zero, with a negative impact on profit. Hence, managers should carefully analyze the potential countereffects of a DTC campaign.

Our conclusions confirm the findings of two large-scale studies on the profit impact of physician- and patient-oriented marketing activities in the U.S. market (Neslin 2001; Wittink 2002). Both studies reveal that, on average, physician-oriented marketing efforts such as detailing generate the highest return on investment. ROI for DTC, however, is very small and may even turn negative.

Implications for society

Health care professionals have been arguing for a long time that DTC may force physicians to prescribe drugs that are not beneficial to the patient's health or that are unnecessary and therefore raise overall drug spending. In such cases, DTC has no beneficial effects to society. European governments seem to believe in these negative welfare effects and ban DTC. The results from this study contribute to solving the issue of whether DTC is indeed expanding demand. They suggest that the power of DTC to expand the market is very limited across all analyzed product categories. Nevertheless, pharmaceutical companies have constantly increased their expenditures on DTC in recent years. Such expenditures may have helped secure or create jobs in the advertising industry.

Detailing is more effective in driving primary demand. This interactive element is focused on health care professionals who are able to evaluate the benefits and threats of a drug therapy. We therefore do not believe that detailing is dangerous to the population's health. However, it may provide incentives to physicians to prescribe drugs that are not required from a medical perspective. In such cases, health care costs rise, with negative consequences for social welfare.

Limitations and future research

Our research has limitations that may stimulate future research. We derive primary demand effects for a broad selection of categories but not for the U.S. pharmaceutical market in total, which is the aggregate of all categories. Hence, we cannot draw conclusions about the impact of detailing, for example, on the country's total drug expenditures. It may be that such an effect does not exist because categories only substitute sales from each other. However, our results still provide important insights in this case. As an example, health care costs rise if a category with expensive drugs is promoted and grows at the expense of other categories that offer drugs of comparable effectiveness but at lower cost.

Our analysis is focused on primary demand effects of pharmaceutical communication activities. We do not consider primary demand effects that may arise from other activities such as product innovation. This may represent a fruitful avenue for future research. Finally, the regulation of pharmaceutical markets is very diverse across countries and generates different market conditions. While the United States has adopted a market-oriented policy, most European countries pursue a rather restrictive policy. It would be interesting to extend the analysis to other countries.

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Notes

1. We acknowledge that an important stream of the marketing literature deals with the estimation of primary demand effects with disaggregate data (e.g., Arora, Allenby, and Ginter 1998; Gupta 1988; Van Heerde, Gupta, and Wittink 2003). Given the focus of this study on aggregate data, we do not discuss these approaches in detail.

2. We note that unlike in other industries, categories for pharmaceuticals are well defined. Consistent with industry practice, we base the definition of categories on the EphMRA Anatomical Classification System (EphMRA 2006).

3. We recognize that our method requires the estimation of more parameters than the conventional approach, when heterogeneous brand sales effects are present. There may be data constellations in which the number of observations available per parameter favors the application of a category sales model. However, we do not believe that such a scenario is very likely. Moreover, the attenuation effect would still be present.

4. The specification test shows that errors do not follow a first-order autoregressive process ($p > .05$).

5. Details on the operationalization of innovativeness classes are given in Sorescu, Chandy, and Prabhu (2003), p. 88.

6. A synergetic cross-price effect seems plausible to us. Due to the inelastic demand for innovative drugs, manufacturers have strong incentives to charge a high innovation premium. New therapeutic alternatives (e.g., the treatment of hypertension with A-II-antagonists) are more effective than older therapies but also more expensive. If prices in such a category go down (e.g., due to the entry of a new innovative drug), the highly innovative therapy becomes less expensive and may shift demand from other categories to the brands in the focal category.

7. Equation 3 is a linear combination of random variables. Hence, a variance estimate is directly available by computing the squared market-share weighted sum of posterior variances of individual brand sales elasticities. For long-term responsiveness measures, however, we need to apply the delta method to obtain a variance estimate.

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