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The authors investigate the changing role of marketing communication over the life cycle of a new product category. They postulate two effects of marketing communication on consumers' choices: an "indirect effect" through reduction of uncertainty about product quality and a "direct effect" (i.e., more is better). The authors expect that the indirect effect is relatively larger in the early, postlaunch stages. They develop a structural model of demand that allows for such temporal differences in the roles of marketing communication. They use a random coefficients discrete choice model with a Bayesian learning process to model physician learning about new drugs and market-level data for the prescription antihistamines category. They find that marketing communication has a primarily indirect effect 6–14 months after introduction but that the direct effect subsequently dominates. The results suggest that firms should follow a pattern of heavier communication at the introduction phase followed by lower levels.

Temporal Differences in the Role of Marketing Communication in New Product Categories

Marketing communication and product experience play significant roles in influencing consumer preferences and behavior in experience good categories that have intangible product characteristics. There is little research that documents the exact role of marketing communication in the evolution of consumers' preferences in such categories that are new to consumers. In this research, we use a modeling approach that enables us to distinguish and examine the evolution of the two major effects of marketing communication since the inception of the category. The two effects we consider are based on existing theories of the role of

marketing communication. The first effect refers to marketing communication that enables consumers to update their prior beliefs and reduce uncertainty about the true quality of the new product through a Bayesian learning process. Because marketing communication affects consumer utility indirectly through perceived product quality, we refer to it as the "indirect Bayesian learning effect," or simply "indirect effect." The second effect consists of all effects that are not indirect (e.g., reminder effects) that influence preferences through goodwill accumulation. Because this effect is manifest in a direct shift in consumer utility, we refer to it as the "direct goodwill effect," or "direct effect."

Our empirical analysis uses data from a category of ethical drugs. In the pharmaceutical industry, direct marketing communication with physicians is usually referred to as detailing. Detailing comprises promotional visits made to physicians by pharmaceutical representatives.¹ The main sources of information considered by physicians to inform their current diagnoses and prescription decisions are detailing, meetings and conferences, and feedback from previous prescriptions. Additional sources of information include word of mouth and journal advertising. Our main focus is the effect of detailing on the evolution of physician prefer-

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¹For a recent multidisciplinary review of detailing in the pharmaceutical industry, see Manchanda and Honka (2005).

ences and resulting prescriptions through the two previously mentioned mechanisms.

Note that our definition of indirect and direct effects loosely maps to the “informative” (indirect) and the “persuasive” (direct)² effects of marketing communication that are documented by structural approaches in the economics and marketing literature.³ Studies that have modeled one or both of these effects include those of Erdem and Keane (1996), Anand and Shachar (2001), Currie and Park (2002), Ackerberg (2003), and Byzalov and Shachar (2004). The findings on the presence of the effects in these studies are mixed. For example, Ackerberg, Currie and Park, and Erdem and Keane find evidence for a predominantly indirect effect. In contrast, Anand and Shachar find evidence for both effects (in a mature product category). Byzalov and Shachar find that risk aversion may explain the direct effect found in studies that assume risk neutrality.

This study is in line with previous research because we allow for both direct and indirect effects. Furthermore, we postulate that the role of detailing is different in the introduction stage of a drug versus its subsequent stages. At the time of a drug’s introduction, a physician’s experience is limited, and it is likely that he or she is uncertain and not well informed about its efficacy (an intangible characteristic that we define subsequently). Thus, detailing is postulated to have a primarily indirect effect in the introductory phase of a drug’s life cycle by helping the physician identify the “true” efficacy of the drug and reducing the uncertainty about this true efficacy. Over time, as the physician learns about the drug and experience develops, the uncertainty about a drug’s efficacy is substantially reduced, and the effects of detailing are likely to be more direct and to dominate the indirect effect. Behavioral research (see Feldman and Lynch 1988; Mitra and Lynch 1995) has also documented that the role of advertising is different for consumers who are familiar with a product versus those who are not. Specifically, this research shows that even after the informative role of advertising has dissipated, there is still a residual role of advertising through effects such as reminders.

As we mentioned previously, the data set for our empirical analysis is from a category of ethical drugs. Our data set consists of aggregate data on second-generation antihistamines (that treat allergies) for the total United States market. A unique feature of this data set is that we observe marketing activities and aggregate physician prescription behavior from the time of introduction of the category. We also observe it for a relatively long period after its introduction. These features of the data enable us to investigate the effects of marketing communication in both the introductory and subsequent stages of the life cycles of the brands in the category. Ethical drugs are particularly suitable to the study of the role of marketing communication on the evolution of preferences because there is substantial uncertainty about how patients respond to treatments. In addition, the

majority of marketing communication dollars are targeted at the physician (Wittink 2002).

We develop a brand-level discrete choice model of demand that allows for category expansion. The model allows for both direct and indirect effects of detailing and also controls for the effects of other promotional activities (e.g., direct-to-consumer advertising [DTCA], meetings, events). We find evidence for both the indirect and the direct effect of detailing on physicians’ prescription behavior. In addition, we find that detailing has primarily indirect effects in the introductory phase (typically 6–14 months after introduction) but that the direct effects dominate subsequent stages. The finding that the direct effects are significant may explain why firms continue to detail long after a drug is introduced. We also find that, on average, physicians are more responsive to detailing than to other promotional activities.

The key contributions of this article are the following: First, it empirically distinguishes between two different effects of marketing communication and finds evidence for both. Second, it documents the temporal aspect of these two effects of detailing (i.e., the indirect effect dominates in the introductory phase of the product life cycle, and the direct effect subsequently dominates). Third, it provides empirical estimates for the length of time for which the indirect effect dominates. Finally, it fills the gap between research that studies new product categories without accounting for the behavioral process by which preferences evolve (e.g., Heilman, Bowman, and Wright 2000) and research that accounts for this behavioral process but does not study new products or product categories (e.g., Anand and Shachar 2001; Erdem and Keane 1996).

DATA

The data we used in this study are for the antihistamines market in the United States, and we obtained them from Verispan Inc., a firm that collects data on prescriptions written by physicians and on marketing activities of pharmaceutical firms. Our data contain monthly observations from April 1993 to December 2001 for the entire United States antihistamines market. We use the data for the three main second-generation antihistamine brands: Claritin (introduced in April 1993), Zyrtec (introduced in January 1996) and Allegra (introduced in August 1996). Clarinex, which is the fourth antihistamine in the category, was introduced in January 2002, and therefore we do not include it in our analysis. For the brands we use in our study, there are a total of 242 brand–month combinations.

As we mentioned previously, a unique feature of this data set is that we observe the category from its inception. Thus, the data do not suffer from the “initial conditions” problem that is common in models of the kind we use. We also observe the data for a fairly long period and at frequent (monthly) intervals. For each brand, we have information on the number of new prescriptions (NRx’s) (no refills), written in that month; the average retail price (per treatment course) for a prescription; and expenditure on detailing, DTCA, and other marketing expenditures (OMEs) such as meetings and events. Verispan collected the NRx and retail price data through a pharmacy retail audit and the data on promotional expenditures for each drug directly from the respective pharmaceutical firms.

²This has also been referred to as “prestige” (Ackerberg 2001) or as a “complementary” (Bagwell 2003) effect.

³There is another stream of literature that infers that advertising is informative (persuasive) if it increases (decreases) price sensitivity and decreases (increases) prices in equilibrium. The studies find mixed results; some find an informative effect (Leffler 1981), and others find a persuasive effect (Hurwitz and Caves 1988; Rizzo 1999).

Table 1 contains descriptive statistics for the data. From the table, it is clear that detailing is the primary form of promotional activity directed at physicians. Expenditure on detailing is approximately six times greater than that on OMEs directed at physicians. The expenditure on DTCA is in the same range as that on detailing. Claritin is the brand with the largest number of NRx's in the category. It is also the highest priced brand and has the highest mean DTCA expenditure. However, Allegra has the highest mean detailing and OME. Table 1 also shows the seasonal effect that exists in this category. There are substantial differences between the number of prescriptions written in the months that constitute the allergy season and the number of prescriptions written in the other months.

MODEL

Prescription Decision

Although the prescription decision is a complex multi-agent process that involves the physician, the patient, and possibly intermediaries such as insurance firms and health maintenance organizations, the final decision is the physician's because the drug is dispensed only on the basis of the physician's prescription. Thus, we abstract away from this multiagent process and assume that there is a single decision maker, who we henceforth refer to as the physician.

We assume that physicians value the health of their patients and that the physicians' preferences map onto a

utility function over the space of treatment options. This may be due to their sense of professional integrity and/or a desire to avoid malpractice suits in the future and to maintain their reputation. When physicians must make a decision on treatment, we assume that they choose the option that gives them the greatest utility.⁴ On the basis of the medical literature (Kelley and Good 1999) and our discussions with physicians, the drugs in this category are considered substitutes, and the use of multiple drugs to treat allergies is extremely rare. Therefore, we assume that physicians make a discrete choice among available options (i.e., they choose only one of the alternatives for a particular patient). Furthermore, we assume that drugs are bundles of characteristics and that physicians have utility over those bundles. Physicians observe these characteristics, but they may be uncertain about some. Given that physicians imperfectly observe one or more of these characteristics before making a decision, they maximize the expected utility of the alternatives at the decision stage.

For our purposes, we assume that physicians have imperfect knowledge about the mean efficacy of the drug. The underlying dimensions that constitute the efficacy of a drug are, among others, how well it treats the condition for which it is prescribed, the severity of the side effects that patients experience, the time it takes to treat the condition, and the patient's posttreatment state of health. Thus, the physician has a belief about the mean efficacy, but this is in the form of a distribution. This belief is updated as the physician learns about the drug through prescription experience and through information received from pharmaceutical firms.

Learning Process

We assume that physicians begin with an initial prior belief about the mean efficacy of the drug when it is first introduced. Note that because physicians are uncertain about the mean efficacy of the drug, this initial prior belief is represented by a distribution. At each time period, physicians use three sources of information to update their prior beliefs about the mean efficacy of each drug in a Bayesian fashion. This information set consists of (1) the feedback received from patients who were prescribed the drug in the last period,⁵ (2) information that pharmaceutical firms provide through detailing, and (3) OMEs directed at physicians. We refer to these as feedback, detailing, and OME signals, respectively.

The following is our list of assumptions about the learning process: First, given that we are not aware of any data source that informs us about the nature of patient feedback (e.g., proportion, frequency, timing), we assume that the number of feedback signals is equal to the number of pre-

Table 1
DATA DESCRIPTIVES

Variable	Brand	Mean	Standard Deviation
Monthly NRx's (in thousands of units): spring allergy season (March–June) ^a	Allegra	823	395
	Claritin	1482	811
	Zyrtec	590	309
Monthly NRx's (in thousands of units): autumn allergy season September–October) ^a	Allegra	628	382
	Claritin	1343	630
	Zyrtec	558	231
Monthly NRx's (in thousands of units): nonseasonal months (January–February, July–August, November–December) ^a	Allegra	532	305
	Claritin	1101	522
	Zyrtec	432	208
Average retail price ^b (\$)	Allegra	39	4
	Claritin	48	6
	Zyrtec	41	1
Monthly detailing expenditure (in thousands of dollars)	Allegra	7334	2906
	Claritin	6802	2473
	Zyrtec	6240	2020
Monthly DTCA expenditure (in thousands of dollars)	Allegra	5263	4187
	Claritin	5531	6423
	Zyrtec	4542	4554
Monthly OME (in thousands of dollars)	Allegra	1242	821
	Claritin	1034	1071
	Zyrtec	1123	879

^aNRx refers to the total number of new prescriptions in the United States.

^bWe report the average retail price for the entire course of a prescription. Prices and all marketing expenditures are deflated by the Consumer Price Index with January 1991 as the base. We obtained the Consumer Price Index data from the Bureau of Labor Statistics at <http://www.bls.gov>.

⁴However, recent research has shown that for chronic conditions, the physician's preferences on the course of therapy may be different from those of the patients (see Fraenkel et al. [2004] and the references therein).

⁵Although we do not have (free) samples in our data, the effect of sampling is captured through the previous prescriptions. Thus, we must assume that feedback from a regular prescription is not systematically different from a sample-based prescription. We capture any residual effect of samples in the econometric error term.

scriptions written in the previous period.⁶ Note that this is a conservative assumption because the mean number of patient trips made annually in this category is less than one (National Center for Health Statistics 2000). Second, we also assume that the numbers of detailing and OME signals in a time period are equal to the number of dollars spent on detailing and OME in that period.⁷ Third, the aggregate nature of our data (i.e., we observe only the total amount spent on detailing or OME by a firm for each time period) imposes the assumption that all physicians receive the same number of detailing and OME signals.⁸ However, we allow the signal content to differ across physicians. Fourth, the nature of our data also imposes the assumption that all signals (detailing and OME) are received at the beginning of the time period of our data. That is, all the information in the details or OME in a particular period is available to the physician at the beginning of the period. Similarly, the feedback signals of the prescriptions written in the previous period are also available at the beginning of each period. Finally, at each stage, we assume that physicians update their beliefs about the efficacy of the drugs in a Bayesian manner; that is, they have a set of prior beliefs based on the information set that is available up to the previous period, and they update this with the information set of the current period to form a set of posterior beliefs. Physicians then use this set of posterior beliefs to make decisions in the current period. This set of posterior beliefs forms the set of prior beliefs for the next period.⁹

Heterogeneity

We assume that physicians are heterogeneous in their responses to various linear characteristics in their utility function (e.g., price). This is likely because each physician can potentially treat a different set of patients. For example, the distribution of the price coefficient could represent the distribution of the mean price coefficient for the patients of different physicians.

Specification: Learning About Efficacy

In this section, we describe the learning process for an individual physician. Let \bar{Q}_{pjt} denote the physician’s belief about the mean efficacy of drug j at time t , where the \sim sign

⁶This is not a problem as long as we are willing to assume that the ratio of feedback signals to prescriptions written remains fixed in every period. In addition, because we assume that the number of feedback signals is proportional to the number of prescriptions in the previous period, this could potentially incorporate other forms of information that are also proportional to the number of prescriptions. We are indifferent about the process through which this feedback is received.

⁷On the basis of our discussion with industry experts, it seems that the cost of a detail is similar across the three firms in our data. Thus, we need to assume a common scaling factor to go from dollars to number of calls. In our case, we set this scaling factor to one (i.e., the number of detailing signals is equal to the number of dollars spent on detailing). Similarly, for OME, we need to assume a common average cost per meeting.

⁸In effect, we must assume that each physician receives a fixed proportion of the total signals in the market and that this proportion is unchanged over time.

⁹Early studies that used a Bayesian learning process to model category-level diffusion include those of Stoneman (1981), Meyer and Sathi (1985), and Roberts and Urban (1988). More recent studies include those of Erdem and Keane (1996), Crawford and Shum (2005), Coscelli and Shum (2004), Mukherji (2002), Ching (2002), Anand and Shachar (2001), Ackerberg (2003), and Byzalov and Shachar (2004).

indicates that it is a random variable from the point of view of the physician. This is conditional on the information set of the physician up to time t . Let \bar{Q}_{pjt} denote the mean of this belief (distribution) at time t , and let σ_{Qjt}^2 be the variance of this belief.¹⁰ Let nd_{jt} , ns_{jt} , and nm_{jt} , respectively denote the number of detailing, feedback, and OME signals for brand j at time t . Let Q_j denote the true mean efficacy of the drug. As we described previously, efficacy is a broad term that includes how well the drug treats the condition, its side effects, and so forth.

At time $t = 0$, we assume that the initial belief of the physician about the mean efficacy of Drug 1 (the only drug in the market) is normally distributed.

$$(1) \quad \bar{Q}_{p,j=1,0} \sim N(Q_0, \sigma_{Q_0}^2).$$

Similarly, in the time period in which a new drug is introduced, we have a similar expression for the initial belief of the physician. Furthermore, for simplicity, we assume that the initial belief has the same distribution for all drugs in the category. Thus, it will have the same mean and variance as in Equation 1.

The i th feedback signal at time t for drug j , which we assume to be normally distributed, is given by

$$(2) \quad R_{pijt} = Q_j + v_{pijt}, \quad v_{pijt} \sim N(0, \sigma_v^2).$$

We also assume that the i th detailing signal for drug j at time t is normally distributed because there is variation across individual physician–detailer interactions. The signal is given by

$$(3) \quad D_{pijt} = Q_j + \omega_{pijt}, \quad \omega_{pijt} \sim N(0, \sigma_\omega^2).$$

Similarly, the i th OME signal for drug j at time t is given by

$$(4) \quad M_{pijt} = Q_j + \eta_{pijt}, \quad \eta_{pijt} \sim N(0, \sigma_\eta^2).$$

Thus, we assume that the detailing, OME, and feedback signals are all normally distributed around the true mean efficacy. The implicit assumption is that these signals are truthful (i.e., they are equal to the true mean efficacy of the drug in expectation). We also assume that these signals are independent, which is an assumption that could potentially be relaxed with richer data that had more variation than our current data set. The variances in Equations 1–4 are unknown parameters.

At the beginning of time t , the physicians’ beliefs are formed by updating their beliefs at time $(t - 1)$ with the feedback, OME, and detailing signals available at the start of time t . Given that the initial prior distribution (i.e., at time $t = 0$ for Drug 1 and the respective time periods when the other drugs are introduced) is normally distributed and all three signals are normally distributed, the self-conjugacy of the normal distribution implies that the posterior belief in any time period would also be normally distributed. Thus, the belief at the beginning of time t is given by

¹⁰Note that this variance does not vary by physician, because the initial prior belief is assumed to be the same for all physicians, and they receive the same number of signals in every period. As Equation 11 shows, the variance of the belief in any period is a function of the variance of the prior and of the number of signals but not their realized values.

$$(5) \quad \tilde{Q}_{pjt} \sim N(\bar{Q}_{pjt}, \sigma_{Q_{jt}}^2).$$

The mean of this posterior belief can be derived as follows:

$$(6) \quad \bar{Q}_{pjt} = a_{jt}\bar{Q}_{pj(t-1)} + b_{jt}\bar{R}_{pj(t-1)} + c_{jt}\bar{D}_{pj(t-1)} + D_{jt}\bar{M}_{pj(t-1)},$$

where

$$(7) \quad a_{jt} = \frac{1}{\sigma_{Q_{jt}(t-1)}^2} / G, \quad b_{jt} = \frac{ns_{jt}(t-1)}{\sigma_v^2} / G, \quad c_{jt} = \frac{nd_{jt}}{\sigma_w^2} / G,$$

$$d_{jt} = \frac{nm_{jt}}{\sigma_\eta^2} / G, \quad G = \frac{1}{\sigma_{Q_{jt}(t-1)}^2} + \frac{ns_{jt}}{\sigma_v^2} + \frac{nd_{jt}}{\sigma_w^2} + \frac{nm_{jt}}{\sigma_\eta^2};$$

$$(8) \quad \bar{R}_{pj(t-1)} = \sum_{i=1}^{ns_{jt}(t-1)} \frac{R_{pjit}}{ns_{jt}} \sim N\left(Q_j, \frac{\sigma_v^2}{ns_{jt}}\right);$$

$$(9) \quad \bar{D}_{pj(t-1)} = \sum_{i=1}^{nd_{jt}} \frac{D_{pjit}}{nd_{jt}} \sim N\left(Q_j, \frac{\sigma_w^2}{nd_{jt}}\right); \text{ and}$$

$$(10) \quad \bar{M}_{pj(t-1)} = \sum_{i=1}^{nm_{jt}} \frac{M_{pjit}}{nm_{jt}} \sim N\left(Q_j, \frac{\sigma_\eta^2}{nm_{jt}}\right).$$

The variance of the posterior belief is given by the following:

$$(11) \quad \sigma_{Q_{jt}}^2 = \frac{1}{G} = \frac{1}{\frac{1}{\sigma_{Q_0}^2} + \sum_{\tau=2}^t \frac{ns_{j\tau}}{\sigma_v^2} + \sum_{\tau=1}^t \frac{nd_{j\tau}}{\sigma_w^2} + \sum_{\tau=1}^t \frac{nm_{j\tau}}{\sigma_\eta^2}}.$$

Note that though the physician knows his or her belief (i.e., the distribution of efficacy) with certainty at each time period, the econometrician does not. This is because the physician observes the realizations of the detailing, efficacy, and OME signals in the information set, but the econometrician does not.

Specification: Utility Function and Share Expression

Physician p's utility of prescribing drug j to a patient at time t is assumed to be a quadratic function of the uncertain mean efficacy belief, which allows for a flexible specification with respect to risk. We specify the utility function as follows:

$$(12) \quad \tilde{U}_{pjt} = \tilde{Q}_{pjt} + r\tilde{Q}_{pjt}^2 + \beta X_{jt} + \gamma_p \text{Price}_{jt} + \xi_{jt} + \varepsilon_{pjt},$$

where

r = the extent of risk aversion for physicians in the category; physicians are risk neutral if r is zero, risk averse if it is negative, and risk seeking if it is positive;

X_{jt} = a (1 × K) vector of observed characteristics for drug j that include season dummies, time trend, and goodwill stocks for detailing, DTCA, and OME; we subsequently describe how these goodwill stocks are constructed;

β = a (K × 1) vector of coefficients, and γ_p is a physician-specific price coefficient; hereinafter, we refer to β and γ_p as the linear parameters;

ξ_{jt} = an unobserved brand and time-specific characteristic that is common across physicians; and
 ε_{pjt} = an i.i.d. error that varies by physician, brand, and time period.

Because the mean efficacy \tilde{Q}_{pjt} is known with uncertainty, the utility is random for the physician. Therefore, the physician maximizes the expected value of this utility function when deciding which drug to prescribe for each patient. This expected utility is given by

$$(13) \quad E[\tilde{U}_{pjt}] = E[\tilde{Q}_{pjt}] + rE[\tilde{Q}_{pjt}^2] + \beta X_{jt} + \gamma_p \text{Price}_{jt} + \xi_{jt} + \varepsilon_{pjt},$$

where the expectation is over the efficacy distribution. Thus:

$$(14) \quad E[\tilde{U}_{pjt}] = \bar{Q}_{pjt} + r\bar{Q}_{pjt}^2 + r\sigma_{Q_{jt}}^2 + \beta X_{jt} + \gamma_p \text{Price}_{jt} + \xi_{jt} + \varepsilon_{pjt},$$

where \bar{Q}_{pjt} and $\sigma_{Q_{jt}}^2$ are defined as in Equations 6 and 14, respectively.

Let the utility of the outside good (i.e., treatment options other than second-generation antihistamines) be given as

$$(15) \quad U_{p0t} = -\kappa t + \varepsilon_{p0t}.$$

For the purpose of expositional convenience, we define the following:

$$(16) \quad \mu_{pjt} = \bar{Q}_{pjt} + r\bar{Q}_{pjt}^2 + r\sigma_{Q_{jt}}^2 + \beta X_{jt} + \gamma_p \text{Price}_{jt} + \kappa t + \xi_{jt}.$$

Note that the presence of the outside good allows for category expansion (i.e., the total sales of second-generation antihistamines are allowed to vary [increase or decrease] over time). The time trend in the utility for the outside good allows for systematic trends in the overall second-generation antihistamines category other than the ones we have explicitly modeled in our learning process.

We assume that the ε_{pjt} terms are i.i.d. extreme value Type I errors. Thus, we obtain the standard Logit probability (McFadden 1973) that physician p prescribes drug j at time t as

$$(17) \quad Pr_{pjt} = \frac{\exp(\mu_{pjt})}{1 + \sum_{k=1}^J \exp(\mu_{pkt})},$$

where J is the total number of brands (J is not constant over time in our data because of the introduction of two new brands). Note that the composite term $\bar{Q}_{pjt} + r\bar{Q}_{pjt}^2 + r\sigma_{Q_{jt}}^2$ in Equation 16 takes the place of the brand intercept term in a typical share model, and therefore, all else being equal, it reflects the probability that physician p prescribes brand j at time t.

Thus, we obtain the aggregate share by integrating this probability over the physicians:

$$(18) \quad s_{jt} = \int Pr_{pjt} d\Psi(\{\tilde{Q}_{pjt}\}, \beta_p | \theta),$$

where ψ is the joint distribution of physician characteristics, which include the mean efficacy terms and the coefficients for observed characteristics, and θ is a vector of parameters for this joint distribution ψ , which includes the variance of the prior belief, the variances of the detailing and feedback signals, and the heterogeneity variances.

Note that the set of physician-specific mean efficacies ($\bar{Q}_{pj,t}$) for the J brands is observed by the physician but not by the econometrician. Furthermore, this random variable is serially correlated because the draw in period t depends on the draw in period $(t - 1)$. This is clear if we consider the expression for $\bar{Q}_{pj,t}$ in Equation 5. In addition, the coefficients β_p are observed by the physician but not by the econometrician.

The vector $X_{j,t}$ is a vector of observed attributes of the brand. In our empirical analysis of the antihistamines category, we include goodwill stock variables for detailing, DTCA, and OME in addition to dummies for the peak allergy seasons in $X_{j,t}$. The goodwill stocks are of the standard Nerlove-Arrow (Nerlove and Arrow 1962) form:

$$(19) \quad D_{j,t} = d_{j,t} + \theta_D D_{j,t-1},$$

where $D_{j,t}$ is the detailing stock of brand j at time t , $d_{j,t}$ is the detailing flow (i.e., detailing expenditure) of brand j at time t , and θ_D is the proportion of the goodwill stock of a period that is carried over.

We construct goodwill stocks for DTCA and OME in a similar fashion. The reason for using goodwill stock is to account for carryover effects in these variables, which may be potentially important. Thus, by entering the detailing stock in the linear specification, we allow for its direct effect on prescription behavior. We have already accounted for its indirect role in the learning process. Thus, we can distinguish these two effects empirically.

There are two allergy seasons: spring (March to June) and fall (September and October). The seasonal variations are clear from Table 1, which shows the substantial difference between mean NRx's in the months that constitute the two allergy seasons and mean NRx's in other months. Therefore, we include a dummy variable for each allergy season in our specification. Word of mouth may play an important role in the physician's learning and prescription process. However, our data do not capture this phenomenon. The time trend in our specification acts as a reasonable proxy for both word of mouth and for the stock of previous prescriptions.¹¹

The scalar $\xi_{j,t}$ is an i.i.d. unobserved characteristic that is common across physicians but varies by brand and time. Note that it is observed by the physician but not by the researcher, and it potentially includes the effect of unobserved marketing activities (e.g., advertising in medical journals).

Identification

Given the set of nonlinear parameters, the identification of the linear parameters (β and γ_p) is straightforward because it requires only the assumption of exogeneity of

drug entry. This is reasonable because drugs can enter the market only after approval from the Food and Drug Administration. To understand how the learning parameters are identified, we first note that the learning-related term $\bar{Q}_{pj,t} + r\bar{Q}_{pj,t}^2 + r\sigma_{Q_{j,t}}^2$, which is constructed from the primitive learning parameters, is identified from the evolution of shares. In the steady state, when most of the learning has already taken place, the variance of the physician's belief becomes zero ($\sigma_{Q_{j,t}}^2 \rightarrow 0$). Furthermore, the mean of the belief converges to the true mean efficacy of the drug ($\bar{Q}_{pj,t} \rightarrow Q_j$), the true mean efficacy for all j . This helps identify the true mean efficacy vector Q_j . The initial shares identify the initial prior mean efficacy Q_0 . An implicit identification restriction imposed is that the efficacy weight is set to one. Alternatively, one of the efficacy terms could be fixed to one; this would enable us to estimate the efficacy weight. The effect of the number of previous prescriptions, the amount of detailing and OME on market shares, and the evolution pattern of market shares identifies the variances of the detailing, OME, and feedback signals.

The identification of the risk aversion parameter depends on differential rates of takeoff of the sequentially introduced brands. If physicians are risk neutral, we should not observe any difference between the rates at which prescriptions of different drugs take off. However, if physicians are risk averse, brands that are introduced subsequently should have a slower takeoff than earlier introductions because at the time of introduction of a brand, the variance of the belief about the new drug is much higher than it is for an established drug. Thus, risk-averse physicians would prescribe the drug at a slower rate initially than would risk-neutral physicians. We cannot identify the initial prior variance with our data, because the key identifying factor for this parameter (i.e., the degree of volatility in initial purchase decision) is observed only at the disaggregate level. Thus, we fix the initial prior variance to one. Because indirect effects are small in the subsequent stages of the product life cycle, we can identify the direct effect on the basis of the latter part of the long time-series data. After we identify the direct effect, we can disentangle the indirect effect from the introductory stages of the life cycle during which both effects exist. Another intuitive way of examining how the two are identified separately is to note that the overall trend in shares identifies the indirect effect, whereas the period-by-period variation in shares identifies the direct effect. The time trend in the outside good utility is also identified because the learning process has a negligible effect in the subsequent stages, whereas the time trend continues to have a role. Finally, the substitution patterns that do not correspond to i.i.d. behavior identify the distribution of heterogeneity (the elements of the variance-covariance matrix of the heterogeneity distribution Σ) for the linear parameters.

ESTIMATION

We estimate our model using aggregate data. To do this, we developed a generalized method of moments- (GMM-) based method. Berry, Levinsohn, and Pakes (1995; hereinafter BLP) developed a GMM-based methodology that enables the estimation of such random coefficient discrete choice models in which prices may be endogenous. However, in our setup, this methodology cannot be directly used,

¹¹Time trend and stock of previous prescriptions are highly correlated (correlation ranges between 97% and 98%). We thank an anonymous reviewer for suggesting this proxy.

because we have the vector of serially correlated efficacy terms in the model, which are functions of the parameters of the model. Therefore, we develop a modification of the standard BLP methodology to estimate our model. (This is described in detail in an appendix, which is available on request.)

From a methodological point of view, we believe that this is the first attempt to develop a GMM-based method to estimate learning models using aggregate data. This is an important contribution because in many product categories, especially ethical pharmaceutical drugs, the kind of individual-level data that Erdem and Keane (1996), Anand and Shachar (2001), and Ackerberg (2003) use is much more difficult to obtain because of legal and industry-specific factors. Thus, in contrast to models that use individual-level data, there are significant differences in both the model itself and the estimation methodology.

We now discuss some estimation issues. Because the BLP methodology enables us to control for the possible endogeneity of prices using instrumental variables, we use producer price indexes (PPIs) for bulk antihistamines, obtained from the Bureau of Labor Statistics, as instruments in our study. These PPIs constitute part of the costs of producing branded antihistamines, and thus they are likely to be correlated with prices. However, they are likely to be uncorrelated with the unobserved product attribute. We use PPIs for up to six lagged periods and interact them with brand dummies to construct our instrument matrix. Given the aggregate nature of the data and the limited number of observations, we specify heterogeneity only on the price coefficient, though in principle we can specify a richer distribution of heterogeneity. Even with heterogeneity only in the price coefficient, we obtain flexible substitution patterns between brands, which is the primary goal of accounting for heterogeneity with aggregate data.

As in the BLP approach, we need to integrate out the unobserved distribution of heterogeneity in the linear parameters across physicians. In addition, we need to integrate out the distribution of efficacy across physicians. Because it would not be feasible to do these integrations analytically, we used simulation methods with 100 draws for the heterogeneity parameters and 100 sets of stacked draws for the serially correlated efficacy-related signals. For each of these draws, we compute the entire efficacy vector. We then obtain the predicted share with a Monte Carlo integration of the individual probabilities for these 100 sets of draws. On the basis of preliminary analyses, we found that the best carryover parameter for the stock variables was 70%. This is similar to the carryover parameters reported in previous studies (see Berndt et al. 1997). This is also consistent with the industry belief that the effect of these expenditures lasts for approximately six months. A carryover of 70% implies that the effect of expenditure on a marketing activity is diminished by approximately 90% in six months. We also reparametrize the detailing and feedback signal variance parameters by exponentiating them in our estimation to ensure that they are positive. Thus, in our parameter estimates, we report the natural logarithms of the respective variances. To account for the outside good, we need an estimate of the potential market size. We assume that the potential market includes all the allergy patients in the United States, which is estimated at 50 million people (American Academy of Allergy, Asthma & Immunology

2001). Finally, we use a Nelder-Mead Simplex method-based minimizer to obtain our estimates, and we use numerical gradients to obtain the standard errors of our estimates.

RESULTS

Parameter Estimates and Elasticities

We present the results of the empirical analysis in Table 2. The table shows that the estimates are mostly significant and have the expected signs. Recall that the main parameters of interest are the variance of the detailing, OME, and feedback signals and the linear parameters (i.e., the coefficients of price and goodwill stocks for DTCA, detailing, and OME).

The first four parameters in Table 2 are the true mean efficacies for the three brands and the prior mean efficacy, respectively. The parameter estimates indicate that the highest efficacy perception is for Claritin, followed by Allegra and Zyrtec. This is consistent with the context because Claritin is the oldest brand in the category and has the highest share. The mean efficacy levels for all three brands are higher than the prior mean efficacy. This implies that there is learning over time. Notably, our results show that Allegra has a higher true mean efficacy level than Zyrtec, even though it was introduced later. This is consistent with the data; the share buildup for Allegra is faster than it is for Zyrtec, and by the end of the data series, Allegra has a higher share than Zyrtec.

The variance parameters for the detailing, OME, and feedback signals are all significant and in the same order of magnitude. Note that these parameters are nonzero by construction. Thus, significance has no meaning but rather suggests that the parameters are estimated tightly. That the three variances are of similar orders of magnitudes suggests that all three sources of information contribute to physician learning. If any of these variances were substantially different from the other, the signal with a much larger variance would play a smaller role in learning than would other signals.

Recall that these signal variance parameters are relative to the initial prior variance, which is set to one. Thus, their

Table 2
RESULTS

Parameter	Estimate (Standard Error)
Allegra true mean efficacy (Q_1)	-2.61* (.01)
Claritin true mean efficacy (Q_2)	-1.05* (.87)
Zyrtec true mean efficacy (Q_3)	-3.20* (1.48)
Prior mean efficacy (Q_0)	-6.49* (2.64)
log(detailing variance) ($\ln[\sigma_0^2]$)	17.85* (1.16)
log(OME variance) ($\ln[\sigma_1^2]$)	17.51* (1.81)
log(feedback variance) ($\ln[\sigma_2^2]$)	17.00* (2.02)
Risk aversion parameter ($r \times 10,000$)	n.s.
Price coefficient ($\beta_p \times 100$)	-55.83* (1.94)
DTCA stock coefficient ($\beta_{DTCA} \times 100$)	n.s.
Detailing stock coefficient ($\beta_{Detailing} \times 100$)	1.55* (.54)
OME stock coefficient ($\beta_{OME} \times 100$)	n.s.
Spring season dummy coefficient ($\beta_{Spring} \times 100$)	36.31* (4.10)
Autumn season coefficient ($\beta_{Autumn} \times 100$)	18.89* (4.94)
Time trend coefficient ($\kappa \times 100$)	.55* (.09)
Price heterogeneity parameter ($\times 100$)	n.s.

* $p < .05$.

Notes: n.s. = not significant.

absolute values do not have any meaning. However, the ratio of the two effects is of interest because it informs us of the relative contribution to learning by these two information sources. Note also that to keep these parameters positive, we reparametrized them as exponents. Thus, the parameter values in Table 2 must be exponentiated before we take their ratios.

The ratio of the detailing, OME, and feedback signal variances is 2.33:1.66:1 (at the point estimates). This implies that a single feedback signal, which is obtained from one previous prescription, is as informative as 2.33 detailing signals and 1.66 meeting signals. Recall that each dollar spent on detailing is one detailing signal. Thus, each feedback signal provides as much information (the reduction in uncertainty about the across-patient mean) as \$2.33 spent on detailing. A more useful comparison would be to examine how much information a single detailing call provides compared with feedback from previous prescriptions. To do this, we must convert the dollars spent on detailing into detailing calls. Although we have not found any published estimates of the cost of detailing, discussions with industry experts revealed that this cost varies between \$60 and \$100 per call. Thus, if we use the \$60 figure, a single detailing call is 26 (60/2.33) times more informative than feedback from a previous prescription. Similarly, if we use the \$100 figure for the cost of a detailing call, we can conclude that a single detailing call is 43 (100/1.90) times more informative than feedback from a previous prescription.¹²

Another way to observe this comparison is to compute the marginal effects of these sources of information on prescriptions written. In Table 3, we report the marginal effects of one extra prescription on the new prescriptions in the next month and that of an extra dollar of detailing and OME

(considering only the learning effect of detailing and OME and disregarding the effect through the linear goodwill term). As the table shows, on average, an extra prescription generates between .0029 and .0058 prescriptions in the subsequent month through the information that the feedback provides about the drug's efficacy. Conversely, an extra dollar spent on detailing generates an average of between .0007 and .0022 new prescriptions through its effect on learning about efficacy, and an extra dollar spent on OME generates between .0014 and .0029 new prescriptions. These numbers may be potentially useful to pharmaceutical firms in terms of allocating dollar promotional expenditures across dollars spent on generating trial (e.g., through product samples) versus dollars spent on detailing.

The risk parameter (r) is not significantly different from zero, suggesting that physicians are risk neutral when prescribing drugs in this category. This is not a surprising result. First, the condition for which the drug is prescribed is not life threatening. It affects only the patient's quality of life. Second, the side-effects profile is relatively mild. The usual side effects, such as dry mouth, fatigue, drowsiness, and dizziness, can cause inconvenience and discomfort, but they do not lead to serious complications. Third, there are no serious interaction effects with other drugs that the patient may be simultaneously using. Because there are no serious consequences of prescribing drugs in this category (see Kelley and Good 1999), it is plausible that physicians are risk averse with respect to drug efficacy. Fourth, the risk may be borne by patients, not physicians.

We now discuss the linear parameters (Table 2). As we expected, the price coefficient is negative and significant. The coefficient for the time trend is positive and significant. As we mentioned previously, it is probably accounting for effects such as word of mouth. The coefficients for the goodwill stocks for detailing, DTCA, and OME are all positive, but only the coefficient for detailing is significant. This reveals an interesting distinction between the two main promotional activities directed at physicians. Although there is an indirect effect of both detailing and OME, only detailing has a direct effect. If we consider detailing a personal selling situation, in contrast to OME, which includes activities such as meetings and events in which experts are invited to deliver talks to a group of physicians, this result is not surprising.

The coefficients for the season dummies are also positive and significant. However, the parameter on heterogeneity in price coefficient is not significant. We conjecture that it is difficult to identify heterogeneity in our data set because there are only three brands and relatively few observations. As we mentioned previously, heterogeneity is identified in such models through the observed substitution patterns. With only three brands among which substitution can take place, the heterogeneity parameter becomes difficult to identify in the data. An alternative specification without the heterogeneity parameter did not affect the results substantially in terms of significance and direction.¹³

The elasticities for detailing, DTCA, and OMEs appear in Tables 4 and 5. We computed the price elasticities, and

¹²Note that we assume that each previous prescription generates feedback. Although it is only a scaling issue for the estimation, it has implications for the comparison of relative informative content of feedback with marketing activities. For example, if a physician receives feedback from one of ten of patients for whom he or she wrote prescriptions, it would imply that a single detailing call is between 2.58 and 4.30 times as informative as a feedback signal. However, because we do not know the proportion of previous prescriptions that generate feedback, we can compare only the relative information content of a previous prescription with that of the marketing activities. We have also confirmed that our assumption does not affect our other results. However, note that the scale of the estimated signal variance adjusts appropriately to the rescaling of the signals, and thus the results are not affected.

Table 3
MARGINAL EFFECT OF LEARNING THROUGH DETAILING,
OME, AND PREVIOUS PRESCRIPTIONS

<i>Number of Extra NRx's (× 100)^a Due to ...</i>	<i>Allegra</i>	<i>Claritin</i>	<i>Zyrtec</i>
One extra NRx in the previous month	.44	.58	.29
One extra dollar spent on detailing	.10	.22	.07
One extra dollar spent on OME	.19	.29	.14

^aThe estimates should be divided by 100 to obtain the number of extra NRx's (e.g., in the first row, .0044, .0058, .0029).

Notes: We considered only the informative effect of detailing when computing the marginal effect of detailing and OME (i.e., we did not consider the direct effect through the goodwill stock).

¹³We compared our model with a series of null models (including a Kalman filter-like model). Our model performed better on both fit and predictive measures in and out of sample. Details on these are available on request.

Table 4
DETAILING ELASTICITIES

Percentage Change in Share ($\times 100$) of ...	For Every Percentage Change in Detailing Expenses of ...		
	Allegra	Claritin	Zyrtec
<i>Indirect Effect Elasticities (Standard Error)</i>			
Allegra	4.54 (2.17)	-.02 (.03)	-.01 (.03)
Claritin	-.02 (.09)	3.86 (1.16)	-.01 (.04)
Zyrtec	-.02 (.09)	-.02 (.03)	3.41 (1.44)
<i>Direct Effect Elasticities (Standard Error)</i>			
Allegra	9.12 (.53)	-.33 (.17)	-.05 (.03)
Claritin	-.09 (.05)	8.67 (.72)	-.04 (.02)
Zyrtec	-.09 (.05)	-.31 (.18)	7.95 (.64)

Notes: The elasticities should be divided by 100. For example, the detailing elasticity for the indirect effect is .0454.

Table 5
OTHER ELASTICITIES

Percentage Change in Expenditure of ...	Own Elasticities: Percentage Change in Share ($\times 100$)		
	Allegra	Claritin	Zyrtec
DTC	1.32 (.07)	1.62 (.13)	1.23 (.09)
OME	3.89 (1.44)	1.91 (1.19)	3.17 (.76)

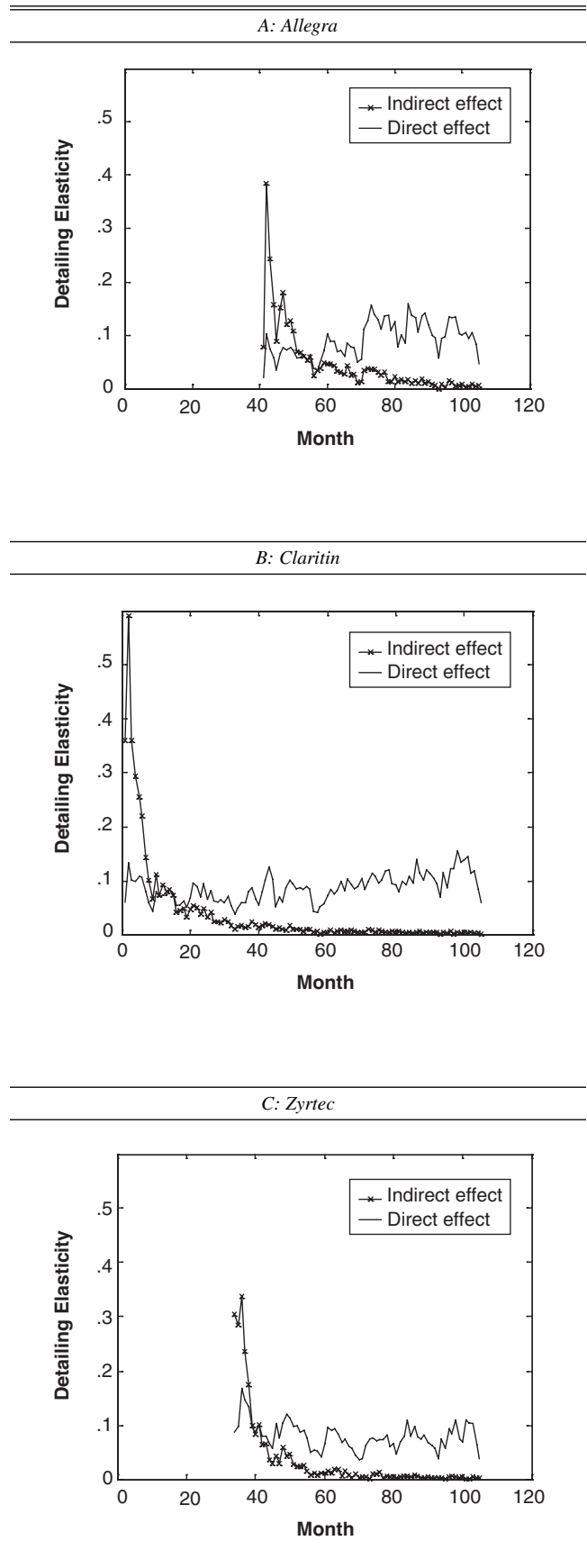
Notes: The elasticities should be divided by 100. The cross elasticities for DTC and OME were small (close to zero).

they are reasonable (the own price elasticities are -2.18 , -2.61 , and -2.25 for Allegra, Claritin, and Zyrtec, respectively). Although there are analytical expressions for elasticities of price and DTCA, the detailing and OME elasticities must be computed by simulating changes in shares with small changes in the detailing or OME expenditure, respectively, in a particular month. This is because detailing and OME affect share both indirectly through learning and directly through the linear effect on utility. The elasticity estimates indicate that demand is most elastic to detailing, followed by OME and then DTCA. The relative ordering of elasticities is in line with prior research: Neslin (2001) and Wittink (2002) report a greater effect of detailing than that of DTCA and OME in their studies across several pharmaceutical categories, and Wosinska (2002) finds the same in the anticholesterol category.

The main result of interest in this study is the distinction between the indirect and direct effects of detailing. We find that the coefficient for the linear detailing goodwill stock is positive and significant. We also find that detailing plays an important role in the learning process. This suggests that both indirect and direct effects of detailing are present in this category. We compute the partial indirect and direct effects of detailing by varying only the number of detailing signals or only the detailing stock, respectively, while keeping the other fixed in our elasticity computations. Note that the total elasticity of detailing is then just the sum of these partial elasticities.

The indirect and direct elasticities of detailing as well as the total elasticities are reported in Table 4. These numbers seem to suggest that, on average, the direct effect is much greater than the indirect effect. However, these averages do not account for the indirect effect decreasing over time,

Figure 1
INDIRECT/DIRECT DETAILING ELASTICITIES OVER TIME



because the physician's belief about the mean efficacy converges to the true mean efficacy of the drug. The direct effect does not have this feature and varies only with the levels of detailing and the shares, thus staying within a relatively narrow band.

Figure 1 shows plots of indirect and direct partial elasticities of detailing over time for the three brands. These plots suggest that the indirect effect becomes negligible by the end of the data series. It takes between 9 and 15 months for this effect to fall below 10% of its peak level. In other words, the learning effect due to detailing is greater than 10% of its peak value for the first 9–15 months, depending on the brand. Across brands, the drop to 10% of peak values is the fastest for Zyrtec (9 months), whereas it takes 15 months for the other two brands. Thus, most of the learning from detailing occurs in this introductory phase of the brand's life cycle.

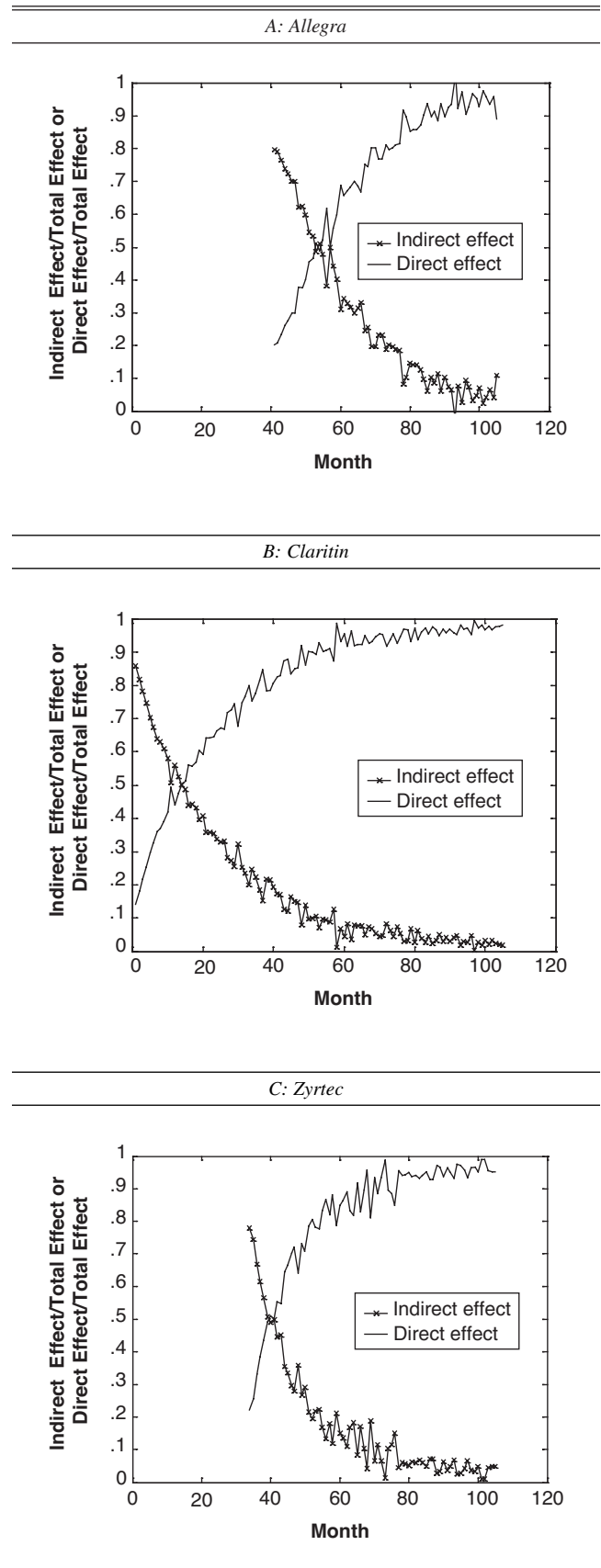
As we mentioned previously, we conjecture that the indirect effect of detailing dominates during the introductory period for the brand but that the direct effect dominates subsequently. To check this, we plotted the indirect and direct effects as proportions of total elasticities of detailing for the three brands (Figure 2). The plots suggest that the indirect effects dominate for the first few months after introduction of the brand, and the direct effects dominate subsequently. The indirect effects dominate for 13 months after introduction for Allegra, 14 months after introduction for Claritin, and 6 months after introduction for Zyrtec. These brand-level differences on how long the indirect effects dominate are related to these brands' patterns of detailing. In the first 6 months after introduction, the detailing for Zyrtec was 152% of the average for the entire data. For Claritin, detailing in the first 6 months was 116% of the overall average, and for Allegra, it was 70% of the overall average. Thus, this initial burst of detailing for Zyrtec causes much faster learning. As a result, the indirect effect converges toward zero much more rapidly for Zyrtec than for the other two brands.

In summary, our results highlight an important aspect of the effect of marketing communication that has not been explicitly studied in prior research. We find evidence in support of our postulate that indirect effects dominate in the initial phase of the brand's life cycle, and direct effects dominate subsequent stages. Furthermore, our finding about the dominance of the indirect and direct effects in different stages of the product life cycle is an important contribution to the literature on the effects of marketing communication.

Managerial Implications

From a managerial perspective, an important issue is the long-term effect of detailing and the consequent implications on allocation of detailing dollars over the life cycle of the drug. The long-term effect of detailing on physician prescriptions arises from three sources. First, higher levels of detailing cause faster learning about drug efficacy. This causes more prescriptions to be written in future periods. We refer to this as the primary indirect effect of detailing. Second, higher levels of detailing also affect future goodwill stock of detailing, again causing an increase in the number of prescriptions written. We refer to this as the primary direct effect of detailing. Third, there is also an indirect effect of detailing that arises from the number of prescriptions written. As the number of prescriptions written

Figure 2
INDIRECT/DIRECT EFFECTS AS PROPORTIONS OF TOTAL
DETAILING ELASTICITIES



(both in the current and future periods) increases, the resultant increase in feedback signals causes a further increase in the rate of learning. We refer to this effect as the secondary indirect effect. Note that the secondary indirect effects come into play only when we consider long-term effects because feedback signals affect only learning for subsequent periods.

We compute long-term elasticities of detailing on physician prescriptions, taking into account these three effects. We report the average monthly long-term elasticities of detailing in Table 6, which we computed by evaluating elasticities for the current and 11 subsequent months and then converting these into monthly averages. These long-term elasticities are substantially greater than short-term elasticities, indicating that detailing effects persist over a reasonable period. We decompose these long-term elasticities into the three component effects: the primary indirect effect, the primary direct effect, and the secondary indirect effect. We compute the changes in prescriptions for the current and 11 subsequent months for each of these components by varying only the respective component and simulating the new prescriptions. The percentage contributions of these partial elasticities to the total elasticities appear in Table 7.

The table shows that the relative strength of the three effects varies across the brands. The primary direct effect dominates for Claritin and Zyrtec, whereas the primary indirect effect dominates for Allegra. These differences arise because the brands are introduced at different times and have different share and detailing patterns over time. Allegra, the final brand to be introduced, has much greater indirect effects at the end of the data series than does Claritin, whose indirect effects have reduced to negligible levels. This is reflected in the greater average contribution of indirect effects (primary and secondary) for Allegra than for Claritin. The secondary indirect effects are relatively small for all brands.

As with short-term elasticities, we expect to find differences in long-term effects, depending on whether the brand is in the introductory stage of its life cycle or in subsequent stages. In the introductory stages, when physicians are not well informed about the brand's efficacy, the indirect effects should have a greater contribution to total effects than should the direct effects, and this should be true in the long run as well. As we showed previously, the short-term indirect elasticities dominate for 9–18 months after introduc-

Table 6

LONG-TERM DETAILING ELASTICITIES: AVERAGE MONTHLY EFFECT

Percentage Change in Share ($\times 100$) of ...	For Every Percentage Change in Detailing Expenses of...		
	Allegra	Claritin	Zyrtec
Allegra	68.23 (19.42)	-1.19 (1.76)	-.20 (.63)
Claritin	-.62 (.29)	58.03 (13.79)	-.35 (.68)
Zyrtec	-.49 (.20)	-1.18 (1.68)	50.64 (14.74)

Notes: For each month, we evaluated the percentage change in NRx's for the current period and 11 subsequent months due to each percentage change in current detailing expenditure. We then converted this annual figure to a monthly average. We report this average to make it comparable to short-term elasticity estimates that we reported previously, which are for the current month only.

Table 7
PERCENTAGE CONTRIBUTIONS OF PARTIAL LONG-TERM EFFECTS OF DETAILING: AVERAGES FOR THE ENTIRE DATA SERIES

Partial Effect	Partial Effect/Total Effect for Brand		
	Allegra	Claritin	Zyrtec
<i>Averages for the Entire Data Series (%)</i>			
Primary effect of detailing on learning	51	37	38
Primary effect of detailing on goodwill stock	47	58	61
Secondary effect due to the change in the number of feedback signals	3	4	1
<i>Averages for the First Six Months After the Introduction of the Drug (%)</i>			
Primary effect of detailing on learning	79	77	66
Primary effect of detailing on goodwill stock	17	16	33
Secondary effect due to the change in the number of feedback signals	4	7	2
<i>Averages for the Past Six Months in the Data Series (%)</i>			
Primary effect of detailing on learning	17	11	16
Primary effect of detailing on goodwill stock	82	87	83
Secondary effect due to the change in the number of feedback signals	1	2	1

tion. Therefore, we computed the average contributions for the first 9 months after introduction for each brand. These numbers also appear in Table 7. As we expected, the primary indirect effects dominate in this introductory phase. Furthermore, we report the contributions due to the three effects in the previous 9 nine months of the data series. In this period, the contributions of direct effects are much greater than they are in the initial phase.

Our findings on the variation of the detailing elasticities over time suggest that it is beneficial for firms to allocate more resources to detailing in the introductory phase, when both indirect and direct effects are present, than in subsequent periods, when only the direct effects are present. In other words, firms should spend more on detailing in the introductory period because it leads to faster learning. However, they may still need to detail in subsequent periods because direct effects also affect prescriptions.

Therefore, we examine the actual detailing patterns for the three brands over time. Beginning with the introduction month, we compute the total detailing expenditure for three blocks of 20 months each. Recall that the first block is approximately the period when indirect effects dominate. In the second block, the direct effects are greater than the indirect effects. In the final block, the indirect effects are almost negligible. The total dollar expenditure for the three brands in three periods is as follows: Allegra: \$73.7 million, \$129.3 million, and \$148.4 million; Claritin: \$99.4 million, \$88.9 million, and \$103.8 million; and Zyrtec: \$123.6 million, \$85.6 million, and \$96.2 million. Notably, only Zyrtec shows a pattern that is similar to our expectation (i.e., high detailing in the introductory period followed by lower detailing). Allegra has low detailing in the introductory

block of months compared with subsequent periods, whereas Claritin exhibits (approximately) constant detailing expenditure over the three blocks. Even in terms of detailing-to-sales ratios, the three brands exhibit differences in their temporal patterns of detailing (Allegra: 53%, 28%, and 18%; Claritin: 37%, 13%, and 8%; and Zyrtec 72%, 25%, and 18%), though these ratios reduce over time for all brands. However, our results predict a reduction in absolute levels of detailing over time because the detailing elasticity reduces over time. Because Allegra and Claritin detailing do not follow the pattern that our results suggest, we conduct counterfactual “experiments” to assess the revenue impact if they had followed the suggested pattern.

Specifically, we investigate how revenues for the first 60 months after introduction would change for Claritin and Allegra if their detailing expenditure was high initially and lower in subsequent months. We reallocate the actual total Allegra and Claritin detailing expenditure across the three time blocks (of 20 months each) in the same proportion as the actual Zyrtec allocation across these blocks. We vary the detailing of one brand at a time and compute the new predicted shares, keeping everything else (including other brands’ detailing expenditure) fixed at actual levels. Because OME also contributes to learning, differences in OME levels across brands could confound the results. Thus, we keep the OME level fixed across brands while conducting this experiment and set it to zero without loss of generality. Our results indicate that compared with actual total revenues, Allegra’s total revenues in the first 60 months would increase by 14.04%, whereas those of Claritin would increase by 4.48%. This is in line with our expectation, because Allegra’s detailing pattern is more different from Zyrtec’s detailing pattern than from Claritin’s detailing pattern. These results indicate that, all else being equal, firms can increase their revenues by optimizing the temporal allocation of their detailing expenditure.

CONCLUSIONS

In this article, we develop a structural model that enables us to describe the role of marketing communication in the evolution of preferences in new product categories. We use a modeling approach that enables us to distinguish and examine the evolution of the indirect and the direct roles of marketing communication from the category’s inception. Using a unique data set that contains observations from the introduction of the category, we find evidence for both indirect and direct effects of detailing. This finding is significant because most prior research has found primarily one effect, but there is no consensus among studies on which effect that was. It is possible that studies that found primarily direct effects used data for mature brands in their empirical analysis. It is natural to expect that indirect effects would be much smaller for mature brands than for new brands.

We also find that the indirect effect dominates in the introductory stages, whereas the direct effect dominates in the subsequent stages. The direct effect becomes greater 13, 14, and 6 months postintroduction for Allegra, Claritin, and Zyrtec, respectively. In terms of resource allocation for detailing over time, these results suggest that firms should follow a pattern of heavier detailing during the introduction phase and lower levels during subsequent stages.

Another contribution of this article is that it bridges the gap in the literature between models for new product categories that are nonstructural with respect to the process of diffusion and models that are structural but do not study new product categories. Finally, from a methodological perspective, we propose and estimate a learning model for aggregate data using a GMM-based method that does not require parametric assumptions about the unobserved attribute and allows for endogeneity of prices.¹⁴

On the basis of our results, we can estimate significant and substantial learning effects due to product experience and promotional activities. We find that a single detailing call is between 26 and 43 times as informative as a single feedback from a patient in terms of learning about the efficacy of drugs. This would partially explain why pharmaceutical firms spend such large amounts of money on detailing. It also suggests that detailing has important positive welfare effects, because doctors learn about efficacy of drugs faster if they are exposed to detailing.

Our study reinforces findings in prior research that the detailing elasticities are much greater than the elasticities of DTCA and OMEs, such as meetings and events. Thus, the results suggest that the most effective means of marketing communication in pharmaceutical categories is detailing. However, this does not explain why many new brands, particularly in the recent past, have spent a lot on DTCA, often comparable to the expenditure on detailing for those brands. This suggests that further work is required to understand the role of these marketing instruments.

Our model has some limitations. First, the aggregate nature of our data imposes a series of assumptions about physician behavior, the learning process, and response heterogeneity. In particular, it does not allow physicians to be forward looking, and it forces us to ignore the presence of intermediaries, such as insurance firms and health maintenance organizations, that may play an important role in the physician’s choice. However, note that high-quality panel data with prescriptions and competitive marketing activity are still difficult to obtain for pharmaceutical categories. Second, our model does not allow for forgetting about efficacy, but we do not expect to find forgetting in our data, because ethical drugs are a high-involvement product category. However, this may be important particularly to non-pharmaceutical categories with a large number of choice alternatives. In other words, consumers may forget about brands if they are not regularly exposed to marketing communication (Mehta, Rajiv, and Srinivasan 2004). Third, the aggregate nature of our data is somewhat restrictive because it does not enable us to identify potential parameters of interest, such as unique prior efficacy belief for each brand, the risk aversion on the part of the patients, and the correlations in the signal errors. Finally, our data do not include all marketing activity directed at physicians (e.g., journal advertising). We hope to address these limitations in further research.

¹⁴It is possible that there could be other endogenous variables in our specification (in addition to price). Our model can accommodate such variables easily. The only limitation of our approach is when the endogenous variable influences the Bayesian learning process. However, we are not aware of any other methodology that could account for endogeneity of such variables. This remains an open question for further research.

REFERENCES

- Ackerberg, Daniel (2001), "Empirically Distinguishing Informative and Prestige Effects of Advertising," *RAND Journal of Economics*, 32 (2), 316–33.
- (2003), "Advertising, Learning and Consumer Choice in Experience Good Markets: An Empirical Examination," *International Economic Review*, 44 (3), 1007–1040.
- American Academy of Allergy, Asthma & Immunology (2001), *The Allergy Report: Science Based Findings on the Diagnosis & Treatment of Allergic Disorders, 1996-2001*, (accessed April 21, 2003), [available at www.theallergyreport.org/reportindex.html].
- Anand, Bharat and Ron Shachar (2001), "Advertising, the Matchmaker," working paper, Harvard Business School.
- Bagwell, Kyle (2003), "The Economic Analysis of Advertising," working paper, Department of Economics, Columbia University, (accessed November 21, 2003), [available at <http://www.columbia.edu/~kwb8/Adchap2003-combined.pdf>].
- Berndt, Ernst R., Linda T. Bui, David H. Lucking-Reiley, and Glen L. Urban (1997), "The Roles of Marketing, Product Quality, and Price Competition in the Growth and Composition of the U.S. Anticancer Drug Industry," in *The Economics of New Goods*, Timothy F. Bresnahan and Robert J. Gordon, eds. Chicago: University of Chicago Press, 277–322.
- Berry, Steven, James Levinsohn, and Ariel Pakes (1995), "Automobile Prices in Market Equilibrium," *Econometrica*, 63 (5), 841–90.
- Byzalov, Dmitri and Ron Shachar (2004), "The Risk Reduction Role of Advertising," *Quantitative Marketing and Economics*, 2 (4), 283–320.
- Ching, Andrew (2002), "Consumer Learning and Heterogeneity: Dynamics of Demand for Prescription Drugs After Patent Expiry," working paper, Rotman School of Management, University of Toronto.
- Coscelli, Andrea and Matthew Shum (2004), "An Empirical Model of Learning and Patient Spillovers in New Drug Entry," *Journal of Econometrics*, 122 (2), 213–46.
- Crawford, Gregory S. and Matthew Shum (2005), "Uncertainty and Learning in Pharmaceutical Demand," *Econometrica*, forthcoming.
- Currie, Gillian R. and Sangin Park (2002), "The Effects of Advertising and Consumption Experience on the Demand for Antidepressant Drugs," working paper, Department of Economics, University of Calgary.
- Erdem, Tulin and Micheal P. Keane (1996), "Decision Making Under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets," *Marketing Science*, 15 (1), 1–20.
- Feldman, Jack M. and John G. Lynch Jr. (1988), "Self-Generated Validity and Other Effects of Measurement on Belief, Attitude, Intention, and Behavior," *Journal of Applied Psychology*, 73 (3), 421–35.
- Fraenkel, Liana, Sidney T. Bogardus, John Concato, and Dick R. Wittink (2004), "Treatment Options in Knee Osteoarthritis: The Patient's Perspective," *Archives of Internal Medicine*, 164 (12), 1299–1304.
- Heilman, Carrie M., Douglas Bowman, and Gordon P. Wright (2000), "The Evolution of Brand Preferences and Choice Behavior of Consumers New to a Market," *Journal of Marketing Research*, 37 (May), 139–55.
- Hurwitz, Mark and Richard Caves (1988), "Persuasion or Information? Promotion and the Shares of Brand Name and Generic Pharmaceuticals," *Journal of Law and Economics*, 31 (2), 299–320.
- Kelley, Cathy and Chester B. Good (1999), *Drug Class Review: Non-Sedating Antihistamines*, (accessed April 21, 2003), [available at <http://www.vapbm.org/reviews/nonsedatingantihistaminesreview.pdf>].
- Leffler, Keith (1981), "Persuasion or Information? The Economics of Prescription Drug Advertising," *Journal of Law and Economics*, 24 (1), 45–74.
- Manchanda, Puneet and Elisabeth Honka (2005), "The Effects and Role of Direct-to-Physician Marketing in the Pharmaceutical Industry: An Integrative Review," *Yale Journal of Health Policy, Law, and Ethics*, forthcoming.
- McFadden, Daniel (1973), "Conditional Logit Analysis of Qualitative Choice Behavior," in *Frontiers in Econometrics*, P. Zarembka, ed. New York: Academic Press, 105–142.
- Mehta, Nitin, Surendra Rajiv, and Kannan Srinivasan (2004), "Role of Forgetting in Memory-Based Choice Decisions: A Structural Model," *Quantitative Marketing and Economics*, 2 (2), 107–140.
- Meyer, Robert J. and Arvind Sathi (1985), "A Multiattribute Model of Consumer Choice During Product Learning," *Marketing Science*, 4 (1), 41–61.
- Mitra, Anusree and John G. Lynch Jr. (1995), "Toward a Reconciliation of Market Power and Information Theories of Advertising Effects on Price Elasticity," *Journal of Consumer Research*, 21 (4), 644–59.
- Mukherji, Prokriti (2002), "A Structural Model of Learning for New Products," working paper, Carlson School of Management, University of Minnesota.
- National Center for Health Statistics (2000), *National Ambulatory Medical Care Survey*, (accessed April 21, 2003), [available at <http://www.cdc.gov/nchs/about/major/ahcd/ahcd1.htm>].
- Nerlove, Marc and Kenneth J. Arrow (1962), "Optimal Advertising Policy Under Dynamic Conditions," *Econometrica*, 29 (114), 129–42.
- Neslin, Scott (2001), *ROI Analysis of Pharmaceutical Promotion*, (accessed April 15, 2005) [available at <http://www.rxpromoroi.org/rapp/index.html>].
- Rizzo, John A. (1999), "Advertising and Competition in the Ethical Pharmaceutical Industry: The Case of Antihypertensive Drugs," *Journal of Law and Economics*, 42 (1), 89–116.
- Roberts, John H. and Glen L. Urban (1988), "Modeling Multiattribute Utility, Risk, and Belief Dynamics for New Consumer Durable Brand Choice," *Management Science*, 34 (2), 167–85.
- Stoneman, P. (1981), "Intra-Firm Diffusion, Bayesian Learning and Profitability," *Economic Journal*, 91 (362), 375–88.
- Wittink, Dick R. (2002), *Analysis of ROI for Pharmaceutical Promotions*, (accessed April 15, 2005), [available at <http://www.rxpromoroi.org/rapp/index.html>].
- Wosinska, Marta (2002), "Just What the Patient Ordered? Direct-to-Consumer Advertising and the Demand for Pharmaceutical Products," working paper, Harvard Business School.