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Understanding Firm, Physician and Consumer Choice Behavior in the Pharmaceutical Industry *

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Abstract

This paper argues that the pharmaceutical industry represents an exciting opportunity to carry out academic research. The nature of the industry allows researchers to answer new questions, develop new methodologies for answering these questions as well as to apply existing methodology to new data. The paper opens with some industry background, then provides a brief overview of some important research areas and discusses the open questions in each area. Issues of data type and availability are also discussed.

Keywords: pharmaceutical marketing, patient compliance, response models, new products, physician networks, pharmaceutical pricing

1. Introduction

The pharmaceutical industry in the United States is a large and important industry—in 2002, its size was estimated at 193 billion.[1] It has grown at a double-digit rate in the last two decades. The actions by participants in this industry have a direct impact on the welfare of consumers and society. This industry spends an enormous amount of money on marketing. For example, it spends more than any other industry on its sales force ($ 7 billion annually) and a very large sum on media advertising ($ 2.8 billion annually). It also spends more on marketing than on R&D (e.g., the top nine firms spend 2.5 times the amount on marketing than on R&D).[2] The objective of this paper is to show that this industry, because of its richness and complexity, provides a fertile ground for academic research. As an added benefit, the potential impact of work in this industry is likely to be high for firms, consumers and policy makers.

The main participants in this industry, besides the end consumer, are manufacturers, physicians, governments, insurers, pharmacy benefit managers (PBMs), wholesalers and pharmacies (retailers). The role of the government varies from country to country and therefore results in varied levels of regulation. In some countries, the government is the primary payer (see Chintagunta and Desiraju, 2005). In others, the US in particular, the majority of patients are insured through private insurance. End consumers pay predetermined monthly insurance fees to health plans and co-payments to pharmacies for each drug. Pharmacy Benefit Managers (PBMs), manage the relationship between the pharmacy and the insurer (see Wosinska and Huckman, 2004). They manage the logistics as well as the transfer of funds from the insurer to the pharmacies. They are compensated by insurers directly for this. Manufacturers sell to wholesalers who sell to pharmacies. Finally, manufacturers pay a rebate to insurers. This rebate is transferred via a PBM which retains part of this rebate as a service fee. This results in a complex alliance based network, with a multiplicity of transactions, prices and rebates.

Given this industry structure, we organize the subsequent discussion around three broad research areas. We first look at the role of the consumer, both during the prescription process as well as after. We then look at the new product development process inside the firm followed by the factors that influence new product adoption by physicians. Finally, we then focus on the roles and effectiveness of marketing instruments in this industry. We then describe the various kinds of data that are available to researchers, followed by concluding remarks.

2. The Role of the Consumer (Patient)

Physicians have traditionally treated patients largely as *passive* participants in a process that affects patients' health outcomes. This model is appropriate for diseases that are acute (e.g., a broken leg) and for patients who believe that the doctor knows best. However, patients now have access to detailed information about diseases and medications, and are increasingly inclined to assert their perspectives especially for chronic diseases. This suggests a multi-agent prescription decision and follow up process that includes compliance with the prescribed course of therapy.

The Prescription Decision

Given that many diseases are chronic in nature, the assumption that there exists a single agent (physician or consumer) maximizing her utility seems strong. There exists some research that demonstrates that the tradeoffs made by physicians in prescribing a course for a patient do not necessarily align themselves with patient preferences (see Fraenkel et al., 2004). An open area of research therefore is the development and testing of models that incorporate the utilities of both the physician and patient in arriving at the prescription decision. For example, Misra (2004) allows for two types of physicians—those who strongly value patient utility and those who value it less—and for two types of patients—new and continuing. He then specifies a model that maximizes utility for the physician-patient combination. The design of systems that allow patients to have a bigger say in the choice of therapy is another open area of research. A system like this should be based around a model that is able to elicit patient preferences for various attributes of a therapy in real-time, quantify the tradeoffs and suggest the most preferred treatment for a patient based on a patient/disease/time-specific utility function (methods to calibrate such functions are well known in the medical and marketing literatures). For example, a practical way to facilitate patient involvement in medical decisions is for HMOs to sponsor the installation of kiosks in physician waiting rooms.

Compliance or Post "Purchase" Behavior

Consumer post-purchase behavior is an important determinant of product usage, satisfaction and repeat purchase behavior. For patients, non-compliance leads to medical complications (Loden and Schooler, 2000) and increased health-care costs (Johnson and Bootman, 1995). For pharmaceutical firms, lost sales, driven by brand switching and negative word of mouth that result from perceived product failure, are estimated at $ 15–20 billion annually (Beavers, 1999). Poor compliance also leads to lower customer retention, resulting in lowered prescription revenue for pharmacy retailers (Huffman and Jackson, 1995; Jackson et al., 1996). Given this, it is not surprising that the compliance problem has been called the holy grail of pharmaceutical marketing (van der Pool, 2003). The medical literature has identified over a hundred social, economic, medical and behavioral factors associated with poor compliance. The important ones are the severity of the condition, salience of the condition, price and

misconceptions and misguided expectations from the therapy (Fincham and Wertheimer, 1985). A surprising conclusion from a multitude of studies is that demographic variables are very poor predictors of compliance when condition specific effects are controlled for (Sabate, 2003).

In terms of the role of marketing on compliance, Bowman et al. (2003) study the determinants of compliance behavior using a unique set of patient diaries. Using a comprehensive set of covariates and a linear latent class model, they find a number of compliance drivers that are consistent with the medical literature and marketing constructs. Their finding that an upcoming physician visit increases compliance is particularly robust. With respect to advertising, they find that different market segments of patients have varied responses (sometimes negative) which they attribute to inflated expectations set by ads. Wosinska (2005) uses a large patient panel to test whether the number of missed therapy-days decreases with the level of DTC advertising expenditure. She finds a positive effect of DTC advertising on compliance for patients taking the competitor brand and a negative effect on compliance for the advertised brand. While this is surprising, the economic significance of both these effects is very small. She hypothesizes that the negative effect is due to the advertising providing information not only about the benefits, but also about the drug's associated risks.

However, many questions still remain in this area. Do differences in channel compliance profiles found in the studies above solely reflect self-selection of patients? The full impact of prices on compliance is also not well understood—the two papers cited above that prices matter. However neither accounts for the fact that patients can choose the level of prices by switching to another brand. In addition, can loyalty programs that exist in consumer product markets be adapted to drug therapy settings?

3. New Products

Pharmaceutical categories are characterized by a large number of new product launches. For instance, around 41 completely new drug molecules were launched every year on average in 1994–2003 (IMS Health). However, the industry faces many unique challenges in developing and commercializing innovations. Most notably, the industry faces high risk (on average one success from 10,000 original compounds), high cost (typically greater than $ 800 million for each successful drug), a long development cycle (12 years on average) with a limited product life (effective patent protection is only 8–10 years). We discuss three areas related to understanding the new product development and adoption process using data from the pharmaceutical industry.

The New Product Development Process

The main advantage of studying new product development (NPD) in this industry is that the process is relatively transparent. This is because each stage (there are four major stages) is overseen by the FDA, which releases all pertinent information about the development process to the public. The main research questions in this area are whether should firms develop their own new products, outsource or build alliances. Also, once this decision is

made, the firm needs to decide on the optimal new product portfolio size and resource allocation?

In terms of the first question, the data suggest that most pharmaceutical firms complement their internal NPD with alliances. These alliances usually result in a license for a promising new drug candidate. Not much is known about whether this is the right strategy and/or the right number/nature of licensing partners and the structure of licensing deals. The current practice is to structure a licensing deal as a contingent claim, where the company pays a fixed fee to the partner after the drug candidate passes each NPD stage. For the second question, there is a growing body of research investigating the resource allocation and optimal portfolio question. Ding and Eliashberg (2002) develop a model that optimizes the new product pipeline for a single market opportunity (pipeline) project. A more comprehensive model with a closed-form solution may be found in Loch and Kavadias (2002). A richer use of dynamic programming techniques in this area is also beginning to emerge. Ding and Eliashberg (2004) use these techniques to explicitly accommodate multi-tier objectives in project selection.

However many research opportunities exist. More work is needed for understanding new product development portfolios in high-risk, high-return industries (such as the pharmaceutical industry). There is also scope to build meaningful decision support systems. Marketing academics could also contribute in calibrating launches using pre-launch forecasting models via a large scale meta-analysis, to help in the early stage valuation of new products (e.g., Hahn et al., 1994). Finally, the use of molecular and chemical information characterizing each product may lend itself to a better current market descriptions that drive improved new product design.

Social Networks and New Product Diffusion

There is increasing interest in understanding the extent of influence consumers have on new product adoption by other consumers i.e., contagion or the "word-of-mouth" effects. While the existence of this effect has been known for a long time, not much is known about the network characteristics (extent and type of influence of "near" versus "far" consumers, effect of "opinion-leaders") on actual behavioral outcomes (time to adopt and usage levels). The pharmaceutical industry offers a unique opportunity in terms of documenting this effect. First, outcomes related to adoption and usage "matter" to industry participants. Second, it is relatively easy to isolate networks (e.g., for most drugs, the size of the physician networks is in the tens of thousands). Third, the industry collects a lot of data recording the events post-launch. Finally, the presence of a multiplicity of (potentially interacting) networks hold the promise enriching our understanding of these effects.

The attractiveness of this industry for studying diffusion phenomena has been noted before. Coleman et al. (1966), in a path-breaking study, found that physician adoption decision was affected by interaction with other physicians. They found, using a combination of behavioral and survey data in four physician communities, that a physician's professional interactions had a larger effect on the time to adoption than social interactions. Burt (1987), using self-reported data from a group of physicians, found that the contagion effect is rather

small in magnitude. Using the same set of data, Strang and Tuma (1993) concluded that the contagion effect is sensitive to the model specification, while Van den Bulte and Lilien (2001) found contagion effects disappeared once marketing efforts (journal advertising) are controlled for. In recent work, Manchanda et al. (2004c) use behavioral data to model time to adoption amongst physicians in a geographically compact area (Manhattan). They control explicitly for marketing directed at physicians (detailing and sampling) as well as other unobserved temporal variables and find that the adoption patterns of physically close physicians has an effect on a given physician's adoption decision. The effect size from contagion is smaller (relative to the effect size from detailing) in the initial months post-launch but becomes larger over time.

There are many open areas for future research here. Combining survey and behavioral data should reveal richer insights into diffusion patterns within physician networks. This can lead to a better understanding of how much firm actions can affect diffusion. For example, there is little research on the effectiveness of opinion leaders (targeted by the pharmaceutical industry). Also, almost all existing diffusion studies in this industry have focused on a network comprising of physicians. This is due to the commonly beheld assumption that physicians make decisions on behalf of their consumers. However, as previously discussed, patients are getting more and more involved in the prescription decision making. Thus, it maybe worthwhile to study the interaction between the gatekeeper network (physician) and the consumer network (patient). To the best of our knowledge, no such research exists, largely due to the data unavailability. As patient data become more available to researchers, this is likely to become less of an issue.

Physician and Consumer Learning

Studies using diffusion models have shown that the role of marketing changes over the product life cycle (Leeflang et al., 2004). There has been some recent interest in providing a structural explanation for this diffusion—that of physician and/or consumer learning. This makes intuitive sense as for a new drug there is considerable uncertainty about its characteristics (efficacy, side effects, drug interactions) at the time of launch. For obvious reasons, both physicians and consumers care about reducing this uncertainty (learning). Modeling this learning is important from a policy point of view as well as for accurately assessing the effect of communication by pharmaceutical firms. Some important aspects of this learning mechanism are (a) the various sources of information through which information is transferred (b) the risk behavior of physicians and patients and (c) whether physicians and patients are forward looking or not. A recent stream of work has estimated Bayesian learning models (Stoneman, 1981) on pharmaceutical data. We describe a few of these studies below (see Table 1 provides a summary overview).

In terms of learning by consumers (patients), Crawford and Shum (2005) estimate a dynamic structural model of demand under uncertainty. They allow forward-looking and risk-averse patients to learn about their match with specific drugs through their own usage experience. They find that patients indeed learn about drugs through their usage experience and that this learning is very rapid, with two-thirds of patients learning about the drug after a

Table 1. Review of research on physician and patient learning about drugs

Study	Naure of the data/ Category	Who is learning?	Source of information	Risk aversion/forward looking behavior	Main question
Ching (2005)	Aggregate data on sales, prices and marketing expenditures for Ace Inhibitors.	Physician	Prescription Experience (public information set), detailing affects the stock of physicians who are informed vs. uninformed about this public information set.	Risk aversion allowed for, no forward looking behavior.	Why does detailing of a drug increases as demand increases for it?
Ching (2002)	Aggregate data on sales, prices and marketing expenditures for multiple categories.	Unspecified (physician/patient combination)	Prescription experience of the physicians	Risk aversion allowed for, no forward looking behavior	Measure the importance of learning vs. heterogeneity
Coscelli and Shum (2004)	Physician panel data on prescriptions for anti-ulcer drugs in Italy.	Physician	Prescription experience of the physicians	Risk aversion allowed for, no forward looking behavior	Explain diffusion of the new anti-ulcer drug *Omeprazole*, accounting for informational spillovers and heterogeneity in informativeness across patients.
Crawford and Shum (2005)	Patient panel data with history of prescriptions for anti-ulcer drugs.	Patient	Consumption experience of the patient	Risk aversion allowed for, forward looking patients	Measure the effects of uncertainty and learning in the demand for drugs.
Currie and Park (2002)	Aggregate data on prescription, prices and marketing expenditures for prescription antidepressants.	Physician/patient combination	Prescription Experience, Detailing	Risk neutrality assumed, no forward looking behavior	Measure the effect of advertising and learning on the demand for prescription drugs.
Mukherjee et al. (2002)	Aggregate data on sales, prices and marketing expenditures for statins.	Physician/patient combination	Prescription Experience, Detailing	Risk neutrality assumed, no forward looking behavior	Empirically differentiate between a direct effect of detailing and one on patient-drug match.

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Table 1. (*Continued*)

Study	Naure of the data/ Category	Who is learning?	Source of information	Risk aversion/forward looking behavior	Main question
Narayanan et al. (2005)	Aggregate data on prescriptions, prices and marketing expenditures for prescription antihistamines.	Physician	Prescription Experience, Detailing, Meetings & Events	Risk aversion allowed for, no forward looking behavior	Measure temporal differences in the role of detailing in the launch phase of a new drug and later on.
Narayanan and Manchanda (2004)	Physician panel data on prescriptions, detailing and patient characteristics for erectile dysfunction drugs.	Physician	Prescription Experience, Detailing	Risk neutrality assumed, no forward looking behavior	Measure individual physician-specific rates of learning and use this for better targeting of detailing at the individual physician level.

single prescription. Their study also suggests that risk-aversion leads to significant amount of persistence in drug choices even after a single prescription.

Narayanan et al. (2005) study how the role of marketing communication for new products changes over time in the presence of learning. They specify a model where physicians learn about the quality of new drugs through marketing communication by firms (detailing; physician meetings) as well as their accumulated usage experience. They find that detailing has a primarily indirect (learning) effect in the initial stages of the product's life cycle and a primarily direct (persuasive) effect later on. Coscelli and Shum (2004) explain the slow diffusion of a new drug in an existing product category through the slow learning (only from patient feedback) about its quality by risk-averse physicians. The physicians' initial pessimism about the drug as well as their risk aversion reduces their propensity to prescribe the drug when it is very new, but as they learn, their probability of prescribing the drug increases. Ching (2005) addresses the question as to why firms increase their advertising efforts for a drug as the demand for it increases. He explains this by noting that detailing has a direct effect on the stock of well-informed physicians.

While much has been done in this area, various aspects of learning have yet to be explored. For example, most learning models have ignored physician learning from other physicians (this could potentially provide a structural explanation for the contagion effect). In addition, there is the possibility of physicians and consumers jointly learning during the course of therapy. Finally, there does not exist much research on differences in learning rates across physicians (for recent work, see Narayanan and Manchanda, 2004).

4. The Role of Price

An important and unusual characteristic of this industry is the complex relationship between price charged by the manufacturer and quantity demanded by the patient (for a description of industry pricing practices, see Kolassa, 1997; also see Berndt, 2002 for an excellent review of this area). This is primarily due to the existence of intermediate parties such as governments or private insurers. Because of private or public (universal) health insurance, patient prices not only map poorly to manufacturer prices (Rosenthal et al., 2003) but demand prices (prices paid by end-users) are *lower* than supply prices (unit revenues received by manufacturers).

The differences in the demand and the supply prices depend (partially) on the role played by the government. In many developed countries, the national government is the insurer and therefore the primary payer for drugs. Many European countries establish a reimbursement cap, usually determined by benchmarking an average or minimum price in a reference group of countries (the reference group varies across countries). In other countries, manufacturers negotiate with national authorities on the basis of clinical, economic and budgetary criteria (for a comprehensive review of regulatory differences in European countries, see Kavanos and Gemmill, 2005). Even in the United States, manufacturers face price interventions when dealing with federal and state government payers. In particular, the Medicaid program for disabled and poor will not pay more than the lowest price given to any private insurer.

Although patient prices are lower than retailer and manufacturer receipts in all countries with public insurance, the variance in these prices is perhaps greatest in the United States. Most people living in the US have employer-sponsored health insurance and around 40 million Americans are covered by Medicaid, but many others lack healthcare coverage, whether by choice or circumstance (this may be alleviated once the Medicare prescription drug benefit for those over 65 kicks in on Jan 1, 2006). Prices paid by publicly and privately insured patients are usually fixed dollar amounts, and there has been a move towards three levels of price depending on the preferred status of the drug as determined by the patient's health plan. As a result, a peculiar empirical setting arises—a patient is likely to face identical prices for preferred drugs A and B and significantly higher prices for non-preferred drugs C and D. Another patient shopping in the same pharmacy may face identical prices for drugs A and C if these are the ones preferred by her health plan, and higher prices for B and D if they are not.

These institutional characteristics have important implications for studying the role of price in pharmaceutical markets. In particular, they raise concerns in using supply prices for estimating demand elasticities. As an alternative, Cleanthous (2002), uses variation in co-payments across consumers' health plans to estimate their willingness-to-pay and shows that this is much higher for patients with health insurance than without. In related work (Cleanthous, 2004), he also finds that the existence of health insurance decreases price sensitivity. This suggests that a multi-dimensional price consisting of (at the very least) the insurance premium and co-payment should be considered to characterize consumer demand. In terms of physician response to price, Misra (2004) finds that physicians are more price sensitive to co-payments (demand prices) for new patients than current patients. Other research has examined the role price plays in the overall marketing mix. Thus, Wosinska (2002) finds that the effectiveness of DTC advertising is higher if the drug is on formulary (i.e., the demand side price is lower). On the other hand, Narayanan et al. (2004) do not find a significant interaction between DTC advertising and the supply-side price. They do find that higher levels of detailing increase (supply-side) price sensitivity.

As noted before, in all international markets, prescription drugs are subject to patents. Once the originator's patent expires, generic manufacturers can bring to market products with the same active ingredient (subject to regulatory approval). The generic product is typically introduced at a much lower price than the supply-price. The differential between the generic prices and the originator drug price has been found to be a function of, among other things, the number of generic manufacturers participating in the market. It can be as high as 80% (Caves et al., 1991). In some European countries, generic manufacturers brand their off-patent copies and are thus able to carry a price premium (Danzon and Furukawa, 2003). In the US, generic substitution of an originator drug quickly reaches over 95% (see Wosinska and Huckman, 2004) largely because of mandatory substitution laws (that require a pharmacist to fill the generic version over the branded one). Although sales of the originator drug fall sharply, supply prices commonly rise as the originator drug focuses on the small inelastic part of the market (Frank and Salkever, 1997). Wosinska et al. (2004) investigate the effectiveness of coupons in inducing adoption of generic drugs. They utilize data from a large randomized study with two interventions. Despite an overall increase in

generic usage, they find no discernable effect of physician coupons and only a limited effect of the educational materials sent to patients.

In conclusion, the role of price in pharmaceutical marketing is an open area for research. Understanding how demand and supply prices influence sales is probably the biggest question. Another open area of research is the flow of payments between the various network members and their impact on both demand and supply prices. Finally, little is known about firms' pricing policies pre-and post-patent expiry.

5. Response Models

There is a significant body of emerging research that focuses on response models (i.e., quantifying the effect of a given instrument) and resource allocation (i.e., across all marketing instruments) models using data from the pharmaceutical industry. There are many reasons why pharmaceutical data are attractive in this domain. First, little is known about the various marketing instruments (detailing, meetings and event, journal advertising, DTC advertising and sampling) that are used in this industry. Second, an interesting facet in this industry is that many of these instruments are set at the *individual* physician level. This allows researchers to potentially quantify the value of targeting. Third, detailing is akin to advertising. As individual exposure data is usually hard to obtain in most industries, data on detailing present a unique opportunity to study this in detail. Finally, the regulatory environment for health care varies across countries. This provides natural variation in the use of marketing instruments.

Studies examining the effects of detailing on sales (prescriptions) using disaggregate data have found a positive but small effect (Gonul et al., 2001; Mizik and Jacobson, 2004; Manchanda and Chintagunta, 2004; Manchanda et al., 2004a). A major issue has been the lack of data on competitive detailing—two studies report a negative effect of competitive detailing (Gonul et al., 2001; Manchanda et al., 2004b). Studies that have used aggregate data have also found similar effects of own detailing (Narayanan et al., 2003; Wittink, 2002; Neslin, 2001). Manchanda et al. (2004b) also find that individual physician responsiveness to detailing is weakly related across therapeutic categories. Although these studies assume detailing to be exogenous, industry participants confirm that detailing is not set at random. Hence recent work has started focusing on this issue. However, new methods are needed to account for this detailing endogeneity, as detailing is set for each individual physician i.e., there is no notion of a common shock (as in Villas-Boas and Winer, 2001). Manchanda et al. (2004a) use a simultaneous equation approach in which they model prescriptions and detailing. In their model, the detailing level for each physician is a function of the physician's base level of prescription *and* responsiveness to detailing. They find that the firm tends to over (under) detail physicians that are (less) more responsive leading to inefficient detailing allocation for about 50% of physicians. Dong et al. (2004) assume that firms set detailing at the profit-maximizing level and derive the estimation equations from such a model. More work is needed on the role of competitive detailing, the effects of detail attributes and detailing setting process over drug portfolios rather than individual drugs. For a detailed review of detailing effects, see Manchanda and Honka (2004).

DTC advertising has also been generally found to have a small and positive effect on demand (Wittink, 2002; Xie, 2003; Narayanan et al., 2003) with some exceptions (Ling et al., 2002). Wosinska (2002) finds that DTC only affects the market share of drugs which have a preferred status on the third party payer's formulary. The effect of DTC advertising seems to be on category expansion—i.e., on patient entry into the category—rather than brand choice of the physician (Rosenthal et al., 2002; Xie, 2003; Narayanan et al., 2003; Izuka and Jin, 2005). However, Steenburgh and Wittink (2004) show that this finding is sensitive to the functional form. Looking at this in more detail, Xie (2003) finds that non-brand specific ads (e.g, help seeking ads) are have a larger effect on patient visits than brand specific ads (e.g., product claim ads). There are many unanswered questions about DTC advertising. For example, the effectiveness of different media is not known. If individual exposure data are available, then the exact behavioral effect of DTC advertising on consumers—on patient visits, on patient requests, and compliance—can be estimated. Finally, the DTC advertising setting process can also be modeled.

Finally, there has been some work that has focused on the comparison of the effectiveness of all the pharmaceutical marketing instruments using metrics such as the return on investment. Estimation of models that estimate the effectiveness of different marketing instruments simultaneously is often hampered by multicollinearity (across the marketing variables). A robust finding from the extant studies is that the ROI from detailing is higher than that from DTC advertising (Neslin, 2001; Wittink, 2002; Narayanan et al., 2004). The former two studies also find the ROI of journal advertising is the highest. Narayanan et al. (2004) and Ling et al. (2002) find a positive interaction effect on demand of detailing and DTC advertising. An interesting discrepancy that seems to be emerging is that ROI measure of marketing instruments using aggregate data are typically very high (over 100%) for this industry. This does not seem to be consistent with the low ROI obtained from models using disaggregate data. A resolution of this discrepancy seems to be an interesting area of research.

International markets vary in their regulation of the pharmaceutical/health care industries. This opens up two kinds of research opportunities. The first pertains to estimating response models within a specific country gives its idiosyncratic regulation pattern. A good example of this may be found in Leeflang et al. (2004) who find that drug prices have no effect on demand in the Netherlands. This is because of the tight controls on the price setting mechanism mandated in that market. The second research opportunity arises from looking at data from the same category across multiple nations and quantifying the effect sizes across different markets as a function of the market characteristics (Chintagunta and Desiraju, 2005; Desiraju et al., 2004).

6. Data

The health care industry represents an attractive source of high quality data for academic research. This is because the industry has a history of capturing marketing and transaction data in a systematic manner. These data have been available at various levels of aggregation–market, territory and individual—for time series that typically range from two to ten years.

The aggregate data typically consist of sales (dollars or units measured as either new or total prescriptions) and marketing instrument data (dollars or units) for detailing, DTC advertising, Physician Meetings and Events (PME), free sampling and journal advertising. Not surprisingly, aggregate data have been more available to academic researchers. Firms that have provided these data are typically the large pharmaceutical manufacturers or market research firms (IMS Health, Verispan/Scott-Levin and Ipsos). Data from within the firm on the new product development process has also been available (e.g., see Ding and Eliashberg, 2002).

The available individual level data focus either on the physician or the patient as the unit of analysis. The physician-centric data are a disaggregate version of the data described above (typically available from firms such as ImpactRx). There are also free third party databases such as the National Ambulatory Medical Care Survey (NAMCS). NAMCS lacks physician level marketing exposure but does have information about diagnoses and not just prescriptions. Patient data has been utilized quite extensively in the healthcare economics literature because they contain data on interactions with physicians, continuing therapy measures (such as compliance), and are perhaps the only source of accurate consumer-level expenditure data (pharmacylevel prices are a compilation of what the insurer and the patient pay). These data have typically not been used in marketing. Other sources of patient are from large panels like the Medical Expenditure Panel Survey (MEPS) or smaller panels with some marketing exposure data (see data from Ipsos used in Bowman et al. (2004)). Ultimately, given the complex and public nature of this industry, there is tremendous potential for researchers to assemble datasets by combining data from various sources to answer important and interesting questions (e.g., Azoulay 2002 who combines market data with scientific studies).

7. Conclusion

In conclusion, we hope that this paper has provided some evidence for the pharmaceutical industry providing many rich and exciting research opportunities. In addition, the potential impact of this research on consumer welfare is likely to be large. The emergence of a significant body of new research in marketing using this industry as a research platform seems to suggest that its time has come.

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Notes

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