An Empirical Study of Physicians' Sample-Dispensing Decisions:

Evidence for the Roles of Experimentation and Subsidy

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Abstract

The practice of dispensing free samples has been widely adopted by U.S. pharmaceutical companies. Despite physicians' significant *gate-keeper and decision-maker* role in dispensing samples, very few studies in the pharmaceutical marketing literature have empirically examined physicians' free-sample dispensing decisions or their influence on future prescription decisions. The primary objective of this paper is to fill the gap in the literature by examining the key determinants in physician sample-dispensing and quantity decisions at the individual-physician level while controlling for targeted marketing activities and unobserved physician heterogeneity. We conceptualize the dual roles of drug samples, experimentation and subsidy, in physicians' prescription decision making, empirically test for the existence of these dual roles, and quantify their long-run sales impact using physician panel data from two therapeutic categories. Our analysis yields strong empirical support for the existence of the dual roles in physician sample-dispensing behavior. Finally, we discuss implications of our findings for pharmaceutical managers and policymakers.

Keywords: Free Samples, Marketing Promotions, Healthcare Industry, Pharmaceutical Marketing.

1. Introduction

The practice of dispensing drug samples has been widely adopted by physicians and pushed forward by the pharmaceutical industry in the United States. Industry-wide studies have shown that sampling has achieved wide acceptance among U.S. pharmaceutical companies and drug samples account for a significant part of these firms' marketing budgets (Dong et al. 2013). Nevertheless, unlike other high-stakes marketing activities targeting physicians, such as detailing visits (Kremer et al. 2008), the effect of this investment on physician prescription decisions remains, at best, an open question for many pharmaceutical executives (Lurker and Caprara 2005).

A long stream of marketing literature studies the effects of free samples in a wide range of product categories, including newspaper subscriptions (Scott 1976), music (Peitz and Waelbroeck 2006), computer software (Kempf and Smith 1998, Kempf 1999), cosmetic products (Ben Amor and Guilbert 2009), and food and beverages (e.g., Gedenk and Neslin 1999, Shiv and Nowlis 2004, and Wadhwa et al. 2008, to name a few). In these contexts, the sample-trial decision and the subsequent product-purchase decision are both made by consumers. Unlike in those product categories, however, pharmaceutical firms cannot dispense prescription drug samples directly to their consumers (patients). Patients have to rely on physicians' decisions regarding whether and what drug samples to try, and, after trying a drug, which brand is prescribed. During this process, physicians play a critical *gatekeeper-and-decision-maker* role in dispensing billions of dollars' worth of samples to patients. As a result, in order to assess the effectiveness of drug sampling, it is essential to understand the factors that influence physicians' sample-dispensing decisions.

The literature has documented multiple rationales that may motivate physicians to dispense drug samples to patients. On the one hand, as the efficacy and tolerability of a drug may differ widely from patient to patient, physicians have incentives to determine whether a drug works for

a patient before prescribing it to him or her. The availability of free samples would allow physicians to "experiment" at a lower cost to patients relative to a full prescription. In other words, drug samples can benefit physicians and patients as a cost-effective[1] way to lower the diagnostic uncertainty. This view of free samples facilitating experimentation has been adopted by two recent marketing papers (Joseph and Mantrala 2009; Bala et al. 2013) as the key assumption in deriving the optimal sampling plan within a game-theoretical framework. On the other hand, physicians often bear a patient's financial needs in mind when making prescription decisions, offering lower-income patients a "subsidy" in the form of free samples. According to a study conducted by the Kaiser Family Foundation, 75% of physicians report that they dispense drug samples to assist patients with their out-of-pocket expenses. This is one of the major reasons pharmaceutical industry representatives have routinely described drug samples as a cost-saving safety net for the poor.

Recently, due to the increased public scrutiny regarding soaring healthcare expenditures, the common practice of dispensing free samples has become one of the frequently debated topics in such popular mass media as the *Wall Street Journal* and MSNBC (e.g., Rabin 2007). The debate centers around the roles of drug samples in prescription decision making, and their long-term consequences on patient welfare. In particular, critics questioned whether drug samples indeed played a "subsidy" role in assisting the most indigent patients as claimed by many physicians and the pharmaceutical industry (Cutrona et al. 2008). Also, critics doubt the long-term benefits of receiving drug samples. There is evidence that shows patients receiving free samples had higher out-of-pocket costs than those who were not given free samples. This is particularly of concern for

[1] We consider free samples "cost effective" for two reasons. First, free samples can save patients the monetary cost associated with filling a prescription. This is true even for patients with insurance, as long as they have a nonzero copayment to fill a prescription for the drug. Second, free samples can save patients time and travel cost associated with filling a prescription at a pharmacy.

low-income patients who might not be able to afford the treatment after they run out of the free samples, leading to discontinuity of treatment (Chimonas and Kassirer 2009). Responding to these criticisms, some U.S. institutions issued various restrictive policies on drug sampling. For example, the University of Michigan Health System has completely banned their physicians from dispensing drug samples to patients (Rabin 2007). Therefore, understanding the role of sampling in physicians' prescription decision—particularly, how it helps patients and influences future sales in a competitive environment—is also of interest to policymakers in deciding whether this common yet controversial practice should be encouraged or restrained.

Despite physicians' significant gatekeeper-and-decision-maker role in dispensing samples, very few studies in the pharmaceutical marketing literature have empirically examined physicians' free-sample dispensing decisions and their influence on future prescription decisions. Existing studies of pharmaceutical sampling have focused largely on evaluating the impact of samples delivered to physicians by pharmaceutical companies on physicians' subsequent prescriptions[2] (e.g., Gönül et al. 2001, Manchanda and Chintagunta 2004, Mizik and Jacobson 2004, Manchanda et al. 2008). To fill this gap, we focus our attention on the key determinants of physician sample-dispensing and quantity decisions, and we study this at the individual-physician level while controlling for unobserved heterogeneity across physicians. To accomplish our objective, we develop an integrated model for the joint brand choice and sample dispensing decision, as well as the sample quantity decision in a hierarchical Bayesian framework. This framework takes into account various patient characteristics that may influence physicians' sample-dispensing behavior

[2] This is partly due to data limitation. Drug samples delivered to the physician's office might not reach patients at all. For example, personal and family use of drug samples has been found to be a rather common practice (Westfall et al. 1997). As a result, the proportion of the samples delivered to physicians that are actually dispensed to patients varies widely across physicians. To evaluate the role of sampling and the underlying motives in physician sample-dispensing decisions, it is critical to have information on the actual dispensed samples. However, this information is not tracked in the more popular prescription databases such as the IMS Health prescription panel data.

while controlling for targeted marketing activities from all competing firms and unobserved physician heterogeneity. In particular, our empirical study is designed to answer two questions. First, among all the patients visiting the same physician, which are more likely to receive drug samples and which are more likely to receive a larger quantity of free samples? In particular, based on empirical findings on these questions, can we detect patterns in physician sample-dispensing behavior that corroborate the dual roles—experimentation and subsidy—of drug samples? Second, what are the long-run effects of free-sample dispensing on a particular physician's future prescription decisions? Do drug samples cannibalize sales or induce more sales from the same physician in the future? Moreover, does the role of free samples, whether it is to facilitate experimentation or to subsidize, moderate the long-run consequence of free-sample dispensing? That is, do samples intended to subsidize the poor impact future sales at the physician level differently from samples intended to experiment on new patients?

We answer the research questions by empirically investigating two prescription-drug categories: proton pump inhibitors (PPI) and erectile dysfunction (ED) drugs.[3] Our empirical analysis yields strong evidence for the existence of the dual roles of drug samples at the individual-physician level in both the PPI and ED categories. First, we find that physicians are more likely to dispense free samples of a particular drug to patients with higher diagnostic uncertainty, consistent with the experimentation role of free samples. We also find that physicians are more likely to dispense free samples to patients who do not have insurance coverage relative to insured patients, supporting a subsidy role of drug samples. Second, we find that the quantity of the samples is

[3] We choose these two categories because they span the spectrum from a painful condition to a lifestyle-related health problem and are among the most sampled therapeutic categories in the U.S. pharmaceutical industry. Including both categories in the analysis helps to ensure that the qualitative nature of our findings is not entirely due to characteristics specific to a particular category. It also demonstrates the variations in effect sizes of the two roles of drug samples across various therapeutic categories.

higher when dispensed to uninsured patients, and relatively lower for patients who were prescribed the drug the very first time. These additional findings further support the existence of the dual roles played by drug samples. Third, we find that in the long run, samples dispensed to new patients will induce future prescriptions, consistent with the notion of experimentation through free trials leading to new-product adoption. However, we do not find a significant effect of samples on future prescription decisions if these samples were subsidizing patients without insurance coverage.

This study offers important insights to pharmaceutical marketers as well as to public policymakers. First, our study provides empirical evidence supporting the dual roles played by drug samples in physicians' prescription decisions and quantifies the impact of these two functions on future prescriptions at the individual-physician level. Pharmaceutical managers need to take both functions into account to improve the long-term performance of targeted sampling campaigns. Second, our study demonstrates that a subsidy role does exist when physicians consider which patients should receive free samples. In particular, our results show that a patient without any insurance is on average five times more likely than an insured patient to receive drug samples, with everything else held constant. In view of this important public function served by drug samples, a complete ban on pharmaceutical companies' sampling practices may not be a socially optimal solution. Instead, public policymakers may devise measures that encourage pharmaceutical companies to provide free medication to indigent patients through more direct channels such as patient-assistance programs.

The remainder of the paper is organized as follows. In Section 2, we review the literature and discuss the theoretical background. We then present our data in Section 3, introduce our model in Section 4, and report the estimation results and discuss managerial implications in Section 5. Finally, we summarize the study, and discuss contributions and directions for future research in

Section 6.

2. Literature Review and Theoretical Background

In this section, we first discuss prior research on the drivers of physicians' free-drug-sample dispensing behavior and explore the roles free samples play in physicians' prescription decisions. Second, we review prior literature that studies the promotional effects of free samples in a more general context, and then discuss how these findings can be manifested in the pharmaceutical industry.

2.1. Drivers of Physicians' Sample Dispensing Behavior

Most research that examines the determinants of physicians' drug-sample-dispensing decisions exists in the medical literature. Two main motives suggested in the medical literature are the experimentation role and the subsidy role (Lurker and Caprara 2005). The experimentation role of drug samples hinges on the belief that free samples are a cost-effective way for a physician to determine the efficacy or side effects of a drug in the treatment of a particular patient when faced with diagnostic uncertainty. The availability of free samples would allow physicians to discover the match between the drug and the patient at a lower cost relative to a regular prescription because free samples are provided without any out-of-pocket expenses from the patient and right in the physician's office. The subsidy role relates to the cost saving to indigent patients through supply of drug samples. Chew et al. (2000) conducted a physician survey to investigate under what circumstances and why physicians dispense drug samples. They find that avoiding cost to the patient is the most often reported reason to dispense drug samples, and evaluating treatment effectiveness under complicated diagnostic conditions is the second most-reported reason. Through a field study, Backer et al. (2000) find that individual physicians vary in their intent when

dispensing samples. In particular, physicians use samples to test for efficacy, as a temporary relief or convenience to the patient, or to save costs for their patients. Building on the premise that drug samples can help to solve the diagnostic uncertainty by facilitating trials, Joseph and Mantrala (2009) take an analytical approach to derive the optimal level of sampling efforts in a duopoly setting. Bala et al. (2013) rely on a similar assumption on physicians' sample-allocation behavior to derive the optimal detailing and sampling plan.

If an experimentation role of drug samples exists, we would expect that a physician will have a higher incentive to dispense drug samples to a patient with higher diagnostic uncertainty. For example, a patient who has never been prescribed a drug before would be more likely to receive free samples for the drug than a patient who has been on that particular drug therapy in the past. This is because the benefit of a free trial or mini-experiment will be much greater for a patient where the drug–patient match value is unknown to the physician than for a patient for whom the physician has some knowledge about the drug–patient match value through her treatment history. Further, in most of the cases, it only takes a few trials to find out whether a drug is working for a patient. Thus, if the physicians' main motive is to experiment when she gives free samples to a new patient, we would expect that the sample quantity will be lower. That is, we expect that conditional on sample dispensing decisions, physicians are more likely to dispense a lower quantity of samples to a patient who has never been prescribed the drug before than a patient who has been on the drug therapy before. To the best of our knowledge, no studies in the marketing literature thus far have empirically tested these predictions.

On the other hand, if drug samples play a subsidy role in physicians' prescription decision, we would expect that an indigent patient (e.g., one with low income or with inadequate insurance coverage) is more likely to receive free samples from her physician. In fact, a number of studies

in the medical literature provide empirical evidence for this view. Taira et al. (2003) show that elderly patients with financial problems are more likely to receive drug samples than other elderly patients. Through a patient survey, Stevens et al. (2003) find that receiving drug samples was more frequently reported in the self-pay/uninsured patients than patients with public aid. Morgan et al. (2006) find that giving out free samples to help patients with financial difficulties has been a common practice among the 397 obstetricians and gynecologists who participated in the study. However, a more recent study by Cutrona et al. (2008) report a somewhat unexpected finding from a patient survey that poor and uninsured Americans are less likely than wealthy or insured Americans to receive drug samples.

We speculate the inconsistent findings in these empirical studies could be due to three reasons. First, the majority of the studies in the medical literature are based on either physician surveys or patient surveys, therefore the findings may be subject to self-interest or other types of bias typically present in self-reported data. Second, the aforementioned empirical studies ignore other factors that may also impact physicians' prescription decisions. The most noticeable of such factors is pharmaceutical companies' promotional efforts targeted at individual physicians.[4] A rich literature in marketing has documented the effect of pharmaceutical promotions, especially detailing meetings, on individual physicians' prescription decisions (e.g., Gönül et al. 2001, Manchanda and Chintagunta 2004, Mizik and Jacobson 2004, Kremer et al. 2008, etc.). Therefore, it is important to consider other factors that may also impact physicians' prescription decisions when analyzing physicians' sample-dispensing behaviors. Third, a correlation exists between

[4] U.S. pharmaceutical companies have a long history of heavy spending in promotional activities, with the combined annual expenditures of $24 billion in 2010, according to an IMS Health report (Krishnan and Yuan 2011). Among various promotional activities employed by the pharmaceutical companies, detailing meetings between sales reps and physicians account for almost 60% of the total promotional spending. In our analysis, we specifically control for detailing visits at individual physician level. However, due to data limitation, we are not able to obtain information on other promotional efforts targeted at individual physicians, such as physician events and meetings. We acknowledge this as a limitation of our study.

patients' socioeconomic status and their chance of visiting a physician when they are ill. According to a report released by the Center for Healthcare Research and Transformation (Young et al. 2013), many uninsured patients live in neighborhoods with little access to primary-care services, and are more likely to use emergency departments as a primary source of healthcare than insured patients. For these reasons, the poor and uninsured might be less likely to visit physicians, so their access to free samples is more limited compared to other patients' access.

We overcome these obstacles by relying on real behavioral data to infer physicians' underlying motivations behind their sample-dispensing decisions while carefully controlling for targeted detailing meetings at the individual-physician level. We also focus on whether indigent patients are more likely to receive drug samples conditional on their visit to the physician. In particular, our study explores whether uninsured patients are more likely to receive free samples and, if they do receive free samples, whether they tend to receive larger quantities compared to other patients receiving free samples. The answers to these questions could add new evidence to the ongoing debates.

The vast majority of the existing marketing studies on the effect of drug samples have focused on evaluating the impact on physicians' prescription choice of samples provided by pharmaceutical firms. However, they have not investigated individual physicians' free-sample-dispensing decisions. One noticeable exception is Venkataraman and Stremersch (2007); these authors find that both detailing and physician meetings have a positive effect on number of samples dispensed by physicians. However, the authors do not explore further the underlying drivers of physicians sample-dispensing behavior (i.e., whether it is due to the experimentation or subsidy role, or both) or how these underlying motivations moderate the long-run impact of drug samples. By incorporating patient characteristics related to physicians' two fundamental motives in free-

sample dispensing in both sample-dispensing model and sample-quantity model, our paper complements Venkataraman and Stremersch (2007) and provides further insights into physician sample-dispensing behavior.

2.2. The Promotional Effects of Samples on Product Sales

A stream of laboratory research has examined sampling's impact on consumer perception of brand images (Hamm et al. 1969; Bettinger et al. 1979), sampling's word-of-mouth effects (Holmes and Lett 1977), and the impact of inconsistencies between the sampling experience and advertising claims (Marks and Kamins 1988). Bawa and Shoemaker (2004) is one of the few studies to empirically examine the sales impact of sampling promotions using field data. They posit three potential effects of free samples on incremental product sales: The acceleration and expansion effects are positive while the cannibalization effect is negative. Using data from two field experiments, they find that free samples can produce long-term effects on product sales, and the effectiveness of free-sample promotions can vary widely even between brands in the same product category.

In a prescription pharmaceutical context, by dispensing samples of a particular drug, physicians may potentially include the drug in their evoked consideration set at future treatment occasions. As a result, the probability of prescribing the drug may increase in the long run due to the inertia in physicians' prescription choices. There exists a rich stream of empirical studies in marketing that examined the effect of various marketing-mix variables (including drug samples provided by pharmaceutical sales representatives) on individual physicians' prescription choices. Gönül et al. (2001), one of the first such studies, report that drug samples have a positive effect on individual physicians' prescription decisions. Similar positive effects of sampling have also been documented in Manchanda and Chintagunta (2004), Mizik and Jacobson (2004), and Manchanda

et al. (2008).

Our paper builds on the previous research by explicitly incorporating free samples' promotional effects on physicians' future prescription decisions. In particular, we expect that the free samples' long-term effect on brand choice might depend on the dispensing physician's underlying motivation. On the one hand, if the purpose is to stimulate trials through experimenting, we speculate a physicians' free-sample dispensing would have a positive effect on her future prescription, as demonstrated in existing studies of the effect of sampling in the pharmaceutical industry. On the other hand, if the main objective is to provide subsidy to an indigent patient, we would expect a negative effect of free-sample dispensing on a physician's future prescription of the same brand, which is similar to the cannibalization effect as shown in Bawa and Shoemaker (2004).

The effect of drug samples on prescription decisions is also frequently discussed in the medical literature. By comparing the prescription behavior of two groups of physicians, Symm et al. (2006) concludes that physicians who distribute samples are more likely to prescribe those sampled medications than their counterparts who do not. Using a different study design and sample, Adair and Holmgren (2005) reached a similar conclusion. One obvious limitation of such studies is that free-sample dispensing was the only determinant considered, while a wide range of other factors might impact physicians' prescription decisions, such as other marketing activities and patient characteristics. In the current study, we address this limitation by explicitly incorporating these other factors in our analysis. In addition, unlike previous studies' almost exclusive focus on physicians' choice to use free samples or not, we also study physicians' sample quantity decision. Examining the factors that affect physicians' quantity decision helps us further disentangle the dual roles free-sample medication might play in physicians' prescription behavior.

3. Empirical Context

In this section, we describe the empirical context for our study. The data were collected and made available to us by ImpactRx, a U.S. pharmaceutical marketing research and consulting company. The data consist of daily prescription and detailing activities reported by a panel of primary care physicians for two therapeutic categories, PPI and ED. The sample data period is from August 2005 to August 2006 for the PPI category, and from January 2005 to December 2005 for the ED category. We focus on the prescription drugs in each category: Aciphex, Nexium, Prevacid, and Protonix in the PPI category and Cialis, Levitra, and Viagra in the ED category. Given that we would like to control for the effects of pharmaceutical companies' sales visits on physicians' prescription decisions, we chose physicians who have received at least one detailing visit during the data period. This leaves a sample of 770 physicians for the PPI category and 742 physicians in the ED category.

The prescription data contains the following decisions made by each physician at each patient visit: (i) the name of the brand chosen, (ii) the treatment mode (prescription vs. sample only), and (iii) the quantity prescribed for the chosen combination of brand and treatment mode. Table 1 describes the market share and shares of free samples and prescriptions for each brand. Table 1(a) lists the results for the four PPI drugs and Table 1(b) lists the results for the three ED drugs in our dataset. Free-sample dispensing activities are substantial in both categories: 22.5% of the total treatments in the PPI category and 38.8% of them in the ED category. The intensity of free-sample dispensing tends to vary from brand to brand. In both categories, the leading brands (in terms of overall market share) tend to have a smaller proportion of treatments using samples only. Table 2 presents the summary statistics on sample quantity conditional on the brand and treatment mode choice decisions, Table 2(a) for the PPI category and Table 2(b) for the ED

category. When samples are dispensed, the quantity is usually smaller than when a prescription is written, on average about half of the prescription quantity. Combined with the fact that sample treatments were dispensed to patients on 22.5% of the patient visits in the PPI category, we can easily calculate that about 12.5% of the total drug sales are actually freely provided to the patients in the PPI category. And the number is even higher, 27.3%, for the ED category. With such a high stake invested in free-sample promotions, it is imperative for pharmaceutical firms to understand the consequences of such practices.

[Insert Tables 1 and 2 around here]

Our data contain rich information regarding patient demographics and treatment conditions. Although we do not observe a patient's full treatment history in the data, we have information on two summary indicators: whether the patient was newly diagnosed with the disease (i.e., a new patient vs. a returning patient) and whether a returning patient was prescribed the same drug before. Summary descriptive statistics of the patient characteristics are provided in Table 3 for the PPI and ED categories. A cross-tab analysis of the distribution of free samples across various types of patients revealed some preliminary model-free evidence supporting drug samples' experimentation role. In the PPI category, for example, we find that 38.6% (3,575 out of 9,258) of the new patients and 35.8% (1,222 out of 3,416) of returning patients who switched to a new treatment received free-sample treatments, whereas only 7.7% (1,018 out of 13,142) of other patients received free-sample treatments. We also obtained some model-free evidence supporting drug samples' subsidy role. We find in our data that 49.8% (432 out of 868) of the patients without insurance coverage received free-sample treatments, whereas only 21.6% (5,383 out of 24,948) of the patients with some insurance coverage (including HMO/PPO/POS plans, Medicare plans, Medicaid plans, and other insurance plans) received free-sample treatments. We conducted the

same analysis using the ED category data and obtained similar model-free evidence to support the existence of both experimentation and subsidy roles of free samples. These data patterns demonstrate at the aggregate level the possible drug-sample roles in facilitating physicians' prescription decisions. In the next section, we develop an integrated model for physicians' sample dispensing and quantity decisions at the individual-physician level. The inferences we draw from this model help us quantify the importance of these two roles for each physician, after controlling for targeted marketing activities and unobserved physician heterogeneity.

[Insert Table 3 around Here]

The data also contain information on firms' detailing visits at individual physician level. The summary statistics are listed in Table 4, Table 4(a) for the PPI category and Table 4(b) for the ED category. In the PPI category, there are altogether 16,049 detailing visits to physicians in our sample, which implies an average physician receives 1.6 detailing visits promoting PPI drugs per month. Among the four brands, Nexium is the most aggressive in detailing promotion, accounting for 31.3% of all the detailing visits followed by Prevacid, whose detailing visits account for 24.1% of the total. Aciphex and Protonix are similar in the total number of detailing visits, each accounting for about 22% of the overall detailing activities in the category. In the ED category, Viagra is the most aggressive brand in detailing promotion, account for 45.3% of all the detailing visits in this category, followed by Cialis (31.4%) and Levitra (23.3%). Comparing Tables 1(a) with 4(a), one can notice that for the PPI category, the ranking of the detailing coincides with that of prescription. This is also true for the ED category. The similarity between the ranking of prescription and the ranking of detailing suggests possible endogeneity in detailing, where detailing allocation decision is not set randomly. An appropriate modeling process is required to correct for this endogeneity, which we will discuss in details in Section 4.

[Insert Table 4 around Here]

4. Model Development

Our model specifies how a physician makes three sample-dispensing-related decisions: which drug to prescribe to a patient conditional on the patient's visit to the physician (conditional brand choice), whether to write a prescription or dispense free samples to the patient without a prescription (conditional mode choice), and how many days of supply to be prescribed or to be dispensed freely to the patient (quantity decision). In the following, we specify how each physician makes these decisions as functions of patient characteristics, marketing activities, and past prescription and sample-usage experiences.

Our model contains three parts. In the first part, for efficiency, we jointly model physicians' brand and mode choices simultaneously. In the second part, we model physicians' prescription quantity decision, conditional on the brand and mode choices. In addition, as documented by existing literature, the problem of endogeneity exists because the firms' detailing visits to physicians are not set randomly (Dong et al. 2009). Therefore, in the third part of the model, we adopted the heuristic approach of Manchanda et al. (2004) and Nair's (2007) limited-information approach to model firm's detailing decisions at the individual-physician level. In the following, we describe each of these three parts in detail.

4.1. Model for Brand and Mode Choices

Conditional on a patient's visit, we assume a physician chooses among brands and between modes (writing a prescription vs. dispensing a free sample) following utility maximization rules. In this framework, each physician's choice conditional on a patient visit is assumed to be governed by the latent utility of choosing a particular brand–mode alternative for that patient. In our empirical context, there are eight alternatives, four brands and two treatment modes. At first

glance, it may seem logical to assume that physicians make these two decisions in a sequential manner. They may choose which brand to prescribe first, and then decide on whether to write a prescription or to dispense a free sample for the chosen brand. Alternatively, they may make the mode choice first (i.e., decide whether to write a prescription or to dispense a free sample), and then decide on a brand conditional on the mode choice. Without knowing the exact decision-making process at the physician level, we rely on statistical measures to determine the proper decision sequence. In particular, we estimated two nested logit (NL) models, each corresponding to one of the two possible sequences in brand and mode choices. In a NL model, the second choice decision influences the first choice decision via the logsum parameter[5] (Ben-Akiva and Lerman 1985, p. 288), which is also called the inclusive value (Greene 2008, p. 848). If the estimate for the logsum parameter is not statistically significantly different from one, the data do not support the sequential-decision assumption, and the multinomial logit (MNL) model is more appropriate for the data.

We estimated each of the NL models under two different assumptions on the logsum parameter: (i) allowing this parameter to be individual specific and (ii) allowing it to be homogeneous across individuals. Our results suggest that in neither case is the coefficient for the logsum parameter statistically significantly different from one. Based on these results, we conclude that the sequential-decision structure is not supported by our data. Therefore, we model physicians' brand–mode choices simultaneously using a MNL model with each alternative defined as the combination of brand chosen and mode selected.

Next, we present the detailed specifications for each alternative. Given that the latent utility specifications are similar across brands, instead of writing out all eight utility functions, one for

[5] The logsum parameter is defined as the ln-transformation of the sum of the denominator in calculating the conditional probability of the choice decision.

each brand–mode combination, we collapse them into two equations, one for each treatment mode. The differences across brands are denoted by the subscript *b* in each equation. In the following, equation (1) specifies the utility function associated with the sample-only mode, and equation (2) specifies the utility function associated with the prescription mode.

$$U_{pbt}^{SO} = \beta_{pb0}^{SO} + \beta_{pd}^{SO} sdtl_{pbt} + \beta_{pls}^{SO} so_{pbs} + \beta_{pz} Z_{pt} + \epsilon_{pbt}^{SO} \quad (1)$$

$$U_{pbt}^{Rx} = \beta_{pb0}^{Rx} + \beta_{pd}^{Rx} sdtl_{pbt} + \beta_{plr} rx_{pbs} + \beta_{pls}^{Rx} so_{pbs} + \sum_{k=1}^{3} \beta_{pk} sor_{pbsk} + \epsilon_{pbt}^{Rx} \quad (2)$$

In equation (1), the latent utility of physician p choosing to dispense a free sample of brand b,[6] at patient visit t is denoted U_{pbt}^{SO}. It is impacted by the following five factors. First, β_{pb0}^{SO} is an intercept term reflecting physician *p*'s intrinsic preference to dispense a free sample of brand *b*. For identification purposes, the intercept associated with dispensing free samples of the brand Aciphex is normalized to zero for all physicians. Second, as documented by Venkataraman and Stremersch (2007), firms' detailing visits could influence individual physicians' sample-dispensing decisions, in addition to its well-documented influence on prescription decisions. To account for the effect of current detailing and the carryover from past detailing, consistent with the formulation of Nerlove and Arrow (1962), we formulate $sdtl_{pbt}$, the detailing stock for a brand *b* and physician *p* at patient visit *t* as follows.

$$sdtl_{pbt} = \lambda^{d} sdtl_{pbt-1} + \sum_{k} \lambda^{l_k} dtl_{pbt_k}$$

λ[7] $\in$ [0,1] is the daily detailing carryover parameter, *d* is the number of days since the last patient

[6] In our data, each company has only one brand in the analysis, so we use *brand* and *company* interchangeably.

[7] We use a grid search method to estimate λ. We find the model has the best fit with the data (judged by the log-marginal likelihood) when λ is set at 0.988, which translates to a monthly carryover rate of 0.7. The result is consistent with past research on detailing (for example, Narayanan et al. 2005 and Manchanda et al. 2008).

visit at time $t-1$. dtl_{pbt_k} represents the kth detailing visit from brand b's sales representative that physician p has received during the period from the last patient visit at $t-1$ to the current patient visit at t. l_k counts the number of days since kth detailing visit to the current patient visit at t. In other words, the detailing stock variable for brand b to physician p at patient visit t is defined as the sum of two components. The first component is the detailing stock at the last patient visit at $t-1$, discounted by the number of days from the last visit at $t-1$ to the current visit at t. The second component is associated with the detailing visits during the period between the last patient visit and the current patient visit. The parameter β_{pd}^{SO} measures how detailing stock from brand b influences physician p's utility to dispense a free sample for the same brand.

Third, to capture possible influence from the last sample usage on the current sample decision, we incorporate a variable so_{pbs}, which counts the number of free samples dispensed by physician p (across patient visits), for brand b, in the 30 days prior to patient visit t. In this notation, to distinguish the time period 30 days before the current patient visit (denoted t), subscript s is used.

Forth, as discussed in Section 2, physicians often consider patients' characteristics when choosing between the sample mode and the prescription mode. Therefore, we incorporate Z_{pt}, the characteristics of the patient who visited physician p at patient visit t, in the utility function. Its parameter β_{pz} represents the incremental utility specific to physician p associated with patient characteristics for the sample mode, as relative to the prescription mode. For this reason, these patient characteristics are incorporated only in the utility function related to the sample mode (as in equation (1)), but not in the prescription mode (as in equation (2)). In particular, we include the following five patient characteristics for the patient visiting physician p at t in Z_{pt}: (i) insurance status, (ii) race, (iii) patient newness, (iv) patient requested any particular drug brand, and (v)

severity of the patient's condition, classified by the physician as mild, medium, or severe. The effects of these variables on the physicians' brand-mode choices are captured by the parameters β_{pz}. These effects are allowed to vary across physicians, but remain consistent across brands.[8]

Finally, ϵ_{pbt}^{SO} is a random error term, which captures other unobserved factors that influence physician *p*'s sample decision for a particular brand *b* at patient visit *t*. ϵ_{pbt}^{SO} is assumed to follow the Gumbel (also called extreme value type I) distribution.

In equation (2), the latent utility associated with the prescription decision for physician *p* choosing brand *b* at patient visit *t* is assumed to be influenced by the following four groups of factors. The first two groups are similar to those in equation (1) for the sample mode, the intercept and detailing stock variables. β_{pb0}^{Rx} is an intercept term that captures physician *p*'s intrinsic preference to prescribe brand *b*, and β_{pd}^{Rx} reflects the influence of detailing stock on physician *p*'s latent utility to prescribe brand *b*. We allow the two detailing parameters, β_{pd}^{SO} and β_{pd}^{Rx}, to be different across modes, to accommodate the possibility that detailing may have differential impact on physicians' prescription and sample-dispensing decisions.[9]

The third group of variables allows physician *p*'s current prescription decision to be influenced by her previous experiences with the same drug through writing prescriptions and dispensing samples to different patients. To allow for such influences, we add five variables describing physician *p*'s past experiences. The first variable is rx_{pbs}, the number of prescriptions

[8] We also estimated an alternative model that allows these parameters to vary across physicians, modes, and brands. We find that the brand-specific estimates are very similar in magnitude and are not statistically different from each other for most of the parameters associated with patient characteristics. Therefore, we chose the more parsimonious model (with the same parameter across brands) as the proposed model.

[9] We restrict these parameters to be the same across brands within the same mode. This formulation is a common practice in choice-model literature (for example, Guadagni and Little 1983; Hardie et al. 1993) because, in a choice model, the cross effects of one brand's detailing on a competitive brand's utility is captured through the underlying structure of the nonlinearity of the logit model framework.

for brand b dispensed by physician p in the past 30 days of patient visit t. Its parameter, β_{plr}, measures the physician-specific state dependence of prescriptions for brand b. Second, we incorporate so_{pbs}, the number of sample-only treatments using brand b dispensed by physician p in the past 30 days of patient visit t. Its parameter, β_{pls}^{Rx}, measures the influence from the past sample experience on the current prescription decision for the same brand for physician p. The superscript, *Rx*, is to distinguish from the parameter in the sample-only utility function, as described in equation (1). In addition, the influence of past sample experience on current prescribing also depends on to whom these samples were dispensed. We capture these differential effects through three percentage variables: (i) the percentage of sample-only treatments in the past 30 days dispensed to patients with no insurance, (ii) the percentage of sample-only treatments in the past 30 days dispensed to new patients, and finally (iii) the percentage of sample treatments in the past 30 days dispensed to returning patients who had not been prescribed drug b before. These variables are denoted sor_{pbsk}, for k = 1, 2, and 3. Their corresponding parameters are denoted β_{pk}, which capture the differential long-term effects of free samples on future prescriptions for the same brand due to different underlying motives at the individual-physician level. The results of these estimates may shed light on debates about the long-term effects of drug samples on individual physicians' prescription decisions. In particular, a positive effect associated with terms (2) and (3) would be consistent with the experimentation role of free drug samples, while a negative effect associated with term (1) is suggestive of the subsidy role played by free drug samples.

Finally, as in the utility function for the sample mode, the additive random error term, ϵ_{pbt}^{Rx}, accounts for all other unobserved factors that might impact physician p's prescription decision conditional on patient visit t. We assume ϵ_{pbt}^{Rx} to follow the iid Gumbel distribution. As a result, conditional on patient visit t, the probability of physician p choosing each alternative, defined by

the combination of brand *b* and mode m (*m* could be either prescription or sample only) can be obtained as

$$P_{pbmt} = \frac{\exp(u_{pbmt})}{\sum_{b'm'} \exp(u_{pb'm't})}$$

4.2. The Impact of Sample Inventory on Model Estimates

Drug samples are usually delivered to physicians' offices by the sales representatives or by mail. The availability of free samples is an important factor that can influence physicians' mode choice and even brand choice decisions, simply because a physician cannot possibly dispense samples of a particular brand if they run out. Unfortunately, we do not observe sample inventory information[10] in our data. Therefore, in this paper, we cannot make a direct assessment of the impact of sample inventory on physicians' prescription and sample-dispensing decision. However, we believe this issue would not invalidate our key empirical findings for three reasons.

First, the probability of sample stockout of a particular brand varies across *physicians* and *patient visits*. The impact of the variation across *physicians* can be captured by the physician–brand–mode-specific intercepts, β_{pbm0} in equation (1). That is, physicians who tend to receive more samples from brand *b* comparing to others will have a higher value of the intercept term β_{pbm0}. Conditional on physician *p*, the variation in sample stockout probability is *random* across patient visits *t*. This is because physician cannot decide whether to give a sample and which brand to select before seeing a patient, they cannot plan ahead for the sample allocations across patients. As a result, all patients visiting the same physician *p* would face the same probability distribution

[10] In fact, as far as we know, no existing studies have ever reported or recorded sample inventory for each drug in each physician's cabinet. Most of the empirical studies on free samples in marketing (e.g., Gönül et al. 2001, Manchanda and Chintagunta 2004, Mizik and Jacobson 2004, Manchanda et al. 2008) rely on the sample provision data (i.e., how many free samples were provided for an individual physician in a given time period) obtained from pharmaceutical companies. However, unlike our study, the sample usage information was not available in these studies, thus making the construction of a sample inventory measure impossible.

of sample stockout. Therefore, this within-physician across-visit variation is considered to be idiosyncratic conditional on a particular patient visit, and therefore can be captured by the random error term ϵ_{pbmt} in equation (1). As a result, although it will lead to a biased estimate for the physician–brand–mode-specific intercepts for the sample mode, β_{pbm0}, the missing information of sample inventory will not bias the other model estimates.

Second, to better understand the sample allocation practice in the industry, we interviewed several physicians and pharmaceutical marketing managers. From our discussions with them, we learned that sales people who visit physicians' offices often try to keep an informal record of sample inventory for their own brand(s) by checking with the physicians or their office staff. The sales people usually try to make sure each physician has some inventory of samples for their own brand(s). This is especially true for major drugs in large therapeutic categories, such as the four PPI prescription drugs[11] and the three ED drugs we study. Based on these inputs, we believe in general the chance of sample stockout should not be very high in the two categories we investigate in this paper.

Third, based on a preliminary analysis of our data, we believe that sample availability is not likely to be the main driver of physicians' mode-choice decisions. In our PPI data, there are 18,987 unique physician-days, with 26.1% of them having more than one patient visit to the same physician on the same day. In these physician-days with multiple patient visits, we observe the same physician made different decisions on treatment mode for different patients on 26% of such occasions. In other words, within the same day when the inventory of sample is likely to be at similar levels, the physician decided to write a prescription for some patients and dispense a free sample to other patients. Our model helps to address the question why physicians give some

[11] For example, during our study period (2005–2006), PPI is ranked as the third largest therapeutic category based on U.S. sales, according to research conducted by IMS Health.

patients free samples while others get prescriptions when samples are available.

Based on the above observations, and due to our data limitation, we cannot directly incorporate the sample availability information into the model. We acknowledge this limitation, and also suggest that it does not influence our key results regarding the dual roles of sampling in influencing physician prescribing behaviors, but it does influence the estimates of the individual-level intercepts. So, our model is not appropriate for forecasting physicians' future prescription and sample-dispensing decisions without the sample availability information.

4.3. Quantity Model

Conditional on the brand and mode choices, the ln-transformation of the quantity dispensed, y_{pbmt}, is specified as follows.

$$\ln(y_{pbmt}) = \gamma_{pm0} + \gamma_{pm1} Z_{pt} + \gamma_{pm2} \ln(sdtl_{pbt} + 1) + \nu_{pbmt}, m = 1,2 \qquad (3)$$

γ_{pm0} captures the physician–mode fixed effect on physician *p*'s quantity decision. Z_{pt} contains the same patient characteristic as in the brand and mode choice model, for the sample mode, presented in equation (1). γ_{pm1} represents a vector of parameters, capturing the impact of observed patient characteristics, and γ_{pm2} captures the detailing effect on physician *p*'s quantity decision. All the above parameters are physician–mode specific. Finally, ν_{pbmt} accounts for all the other unobserved (to the econometrician) variables that might impact physician *p*'s prescription quantity decision for brand *b*, mode *m* (write prescription or dispense free sample). Note that the quantity model is conditional on the brand–mode choice. For each brand, the number of data points to estimate the quantity model is different between the two modes. Therefore, equation (2) actually represents 2 separate regressions, one for each mode. And each regression is estimated by pooling data from all four brands to improve the efficiency of the parameter estimates (as compared to

estimating each brand separately).

4.4. Detailing Model

Existing literature has documented that detailing efforts targeted at the individual-physician level are not set randomly, and ignoring the nonrandomness of these marketing variables in understanding physicians' prescription decisions will lead to biased estimates on the effects of the marketing variables. To control for the endogeneity of these physician-level marketing variables, we combine the method proposed by Villas-Boas and Winer (1999) in the context of choice models with the heuristic approach suggested by Manchanda et al. (2004). As the number of detailing visits to each physician by each brand in each month is an integer or zero, we assume it follows a Poisson distribution with parameter λ_{pbs}. s indicates the 30-day prior to each patient visit t in the other two models. λ_{pbs} is specified with a log-link function:

$$\ln(\lambda_{pbs}) = \alpha_{pb0} + \alpha_{b1}\beta_{pb0}^{Rx} + \alpha_{b2}\beta_{pd}^{Rx} + \alpha_{bb}\ln(dtl_{pbs-1} + 1) + \sum_{b' \neq b} \alpha_{bb'}\ln(dtl_{pb's-1} + 1) + \mu_{pbs} \quad (4)$$

In this specification, β_{pb0}^{Rx} is the intercept and β_{pd}^{Rx} is the detailing parameter for the prescription mode, as specified in equation (2). Note that, in the brand–mode-choice model, we estimate detailing parameters for each treatment mode, while in this model we only allow the detailing parameters for the prescription mode to influence firms' detailing decisions for each physician. This reflects the firms' targeting strategy based on their understanding of how each physician's prescriptions are impacted by their detailing efforts. According to an industry expert who provided us the data, most pharmaceutical companies do not have a way to track how the free samples are dispensed by the physicians, so it is unlikely they use that information in making their detailing decisions at the individual-physician level. Therefore, we do not incorporate the response

parameters for the sample mode as a variable in the detailing model. This is also consistent with the heuristic approach proposed by Manchanda et al. (2004) where a brand's physician-level detailing is influenced by a physician-specific intercept for prescription (β_{pb0}^{Rx}) and the physicians' response to detailing for that particular brand (β_{pd}^{Rx}).

Up to now, all the variables in the detailing model are time invariant. To account for the variation in the number of detailing calls over time, we also incorporate two sets of time-variant variables (Dong et al. 2011). First, to account for the consistency of a company's detailing decision over time at the individual-physician level, detailing from the previous 30-day period is incorporated in the model with an ln-transformation. In equation (4), dtl_{pbs-1} represents the number of detailing visits received by physician *p* from brand *b*, during the period between 60 days before and 30 days before the current patient visit at *t*. Second, according to Leeflang and Wittink (1992, 1996), companies' detailing decision may also be influenced by the competitor's detailing decision in the last time period, we incorporate the ln-transformation of the lagged competitive detailing, which is operated as the total number of competitors' detailing visits for physician *p* during the 30-day period between 60 days before and 30 days before. In both cases, 1 is added to each variable before taking the natural log, to allow the observed lagged prescription and competitive detailing to take the value 0. Finally, μ_{pbs} accounts for all other unobserved (to the econometrician) factors that might impact the firm's detailing decision targeted to each individual physician. We assume these random factors to be correlated across brands—i.e. $\mu_{pbs} \sim N(0, \Sigma_{\mu})$. The covariance matrix Σ_{μ} is estimated, and its dimension is the same as the number of brands in the model (4 for PPI, and 3 for ED in our empirical analysis).

In the detailing model, the ln-transformation of the Poisson parameter λ_{pbs}, contains a multivariate normal component. This structure makes the number of detailing visits follow a

multivariate Poisson-lognormal distribution. As discussed in Aitchison and Ho (1989), this model framework has desirable features compared to a regular Poisson model (Cameron and Trivedi 1998), including that (i) it does not restrict the variance to be equal to the mean as a regular Poisson model does, it allows for dispersion; (ii) it also allows for an over-proportion of zeros; and finally, (iii) it allows for correlations among detailing visits across brands. For example, when a doctor happens to be out of her office during a period of time, the number of detailing calls she received in that period will be low for all brands, which will lead to correlations among the detailing visits across brands. Our model captures such correlations.

4.5. Connections among All Three Models

We cast our model in a hierarchical Bayesian framework to capture the unobserved heterogeneity among the response parameters and to simultaneously estimate all three models together for enhanced estimation efficiency. The parameters in both the prescription and quantity models are estimated at the individual-physician level, and they share some common variables, such as patient characteristics. We allow all parameters in these two models to be correlated, assuming they jointly follow a multivariate normal distribution:

$$\left\{\begin{matrix}[\beta_{pbm}] \\ [\gamma_{pm}]\end{matrix}\right\} \sim N(A, \Sigma).$$

Here $[\beta_{pbm}]$ refers to all the individual-level parameters for each brand–mode from the brand and mode choice model (equation (1) and (2)), $[\gamma_{pm}]$ refers to the individual-level parameters for each model (pooled across brands) from the quantity model (equation (3)). The mean vector, A, and the covariance matrix, Σ, are to be estimated.

All three models are related through (i) simultaneity between the brand–mode–choice model, the quantity model, and the detailing allocation decisions and (ii) correlations among the

parameters between the brand–mode–choice model and the quantity model. In estimating the model, we adopt a full information-likelihood approach to estimate all model parameters simultaneously. The likelihood function consists of the likelihood from all three models, as shown below.

$$L = \prod_{pbmt} \left(P_{pbmt}^{Y_{pbmt}} | dtl_{pbt}, \beta_p \right) \times f\left(y_{pbmt} | \gamma_{pm} \right) \times f\left(dtl_{pbt} | \alpha_{pb} \right)$$

In this likelihood function, the first component is associated with the MNL model for the brand–mode choice, where Y_{pbmt} is a dummy variable indicating the choice decisions. In particular, if physician *p* chooses brand *b* mode *m* (prescription or sample only) during patient visit *t*, $Y_{pbmt} = 1$. Otherwise, it takes the value 0. The second component is associated with the quantity model, conditional on brand–mode choice. The last component is associated with the detailing model, to control for the endogeneity of detailing.

Proper but diffuse priors of the model parameters are employed. The prior for the population level mean of the individual parameters is $\mathrm{A} \sim \mathrm{N}(0, 100I)$, for the covariance matrix $\Sigma \sim IW(n_0, n_0 I)$. n_0 is the scale parameter of the inverted Wishart distribution, defined as 2 plus the total number of parameters to be estimated. For our model, there are 24 parameters in $[\beta_{pbm}]$ and 20 in $[\gamma_{pm}]$, as a result, $n_0 = 46$. In addition, the parameters in the detailing model are defined following a multivariate normal distribution with a diffuse prior—$[\alpha] \sim N(0, 100I)$. To estimate all the model parameters simultaneously, data augmentation (Tanner and Wong 1987) and Markov Chain Monte Carlo (MCMC; Geman and Geman 1984) methods are employed to obtain individual-level estimates efficiently. In estimation, 80,000 draws were simulated in the MCMC, with the last 30,000 draws used to obtain the summary statistics for the estimation results. The results are summarized in the next session.

5. Estimation Results

In this section, we report and discuss the estimation results from both the PPI and ED categories. We first discuss the parameter estimates from the PPI category in detail and then present the results from the ED category focusing on the similarities and differences in the estimation results across these two categories.

5.1. Results from the PPI Category

We report the estimation results from the PPI category in the third column of Tables 5 and 6, to the left of those from the ED category, and also in Table 7(a). Table 5 reports the population-level mean[12] of parameter estimates as well as the (5%, 95%) interval for each parameter from the MNL brand–mode choice model. The parameter estimates associated with the sample mode are presented in the top section of Table 5, followed by the parameter estimates associated with the prescription mode. The results for the PPI category show that, consistent with the extant literature, a focal brand's detailing effort positively influences physicians' likelihood of prescribing the brand. However, it does not have a significant effect on her likelihood of dispensing samples.

[Insert Table 5 around Here]

The parameters related to patient characteristics help us address the question, "Who gets free samples?" In other words, these parameters indicate the impact of these observed characteristics on the patients' likelihood of receiving free samples, as compared to receiving

[12] Given the unavailability of patient identity, although we have information on patient characteristics for each visit, we do not know whether the different visits are made by the same or different patient. As a result, the parameters of the observed patient characteristics are not at the individual-patient level, but at the individual-physician level, while pooling across all patients that visited the particular physician. This helps identify, conditional on the physician, which patients are more likely to obtain free samples relative to other patients visiting the same physician. In addition, it also allows us to study the heterogeneity in doctors' decisions when dispensing free samples.

prescriptions. We find that among the four groups of patients with different insurance statuses, those without any insurance coverage have a much higher chance of receiving free samples than other patients. In other words, more indigent patients are more likely to get free samples, suggesting that samples are provided as a way to *subsidize* these patients' medical expenses. At the first glance, this finding seems to contradict Cutrona et al. (2008) in which the authors find that uninsured Americans are less likely than insured Americans to receive drug samples. This inconsistency could be due to the fact that our estimation result is conditional on patient visit, while the analysis conducted in Cutrona et al. (2008) is not. The lower probability of accessing medical care due to financial difficulty by the uninsured patients might hinder their opportunity to obtain samples from physicians, therefore leading to an overall lower probability of receiving samples. What our results show is that conditional on patient visit, physicians are more likely to dispense drug samples to patients without insurance than to patients with insurance, which is consistent with the findings in Chew et al. (2000).

The parameters associated with new patients and with returning patients receiving new treatments are both positive and statistically significant, suggesting that patients with higher diagnostic uncertainty are significantly more likely to receive samples than those with lower diagnostic uncertainty, i.e., returning patients who are not changing their treatments. This finding is consistent with the notion that free samples facilitate experimentation. The results also show that both race and patient request influence the physician's decision in sample dispensing. In particular, patients who requested a specific drug are less likely to receive samples compared to those who did not make a request. This finding is also consistent with the experimentation role of free samples. When a patient requests a specific drug, it is likely that there is some information regarding the fit between the drug and the patient. In this case, physicians are less likely to dispense

a sample to experiment with the patient than when the patient did not request any specific drug.

The long-term effects of samples on future prescription are captured through five lagged variables in equation (2), with two for the base effect and three for the differential effects of samples due to different underlying motives. Consistent with the literature, we find a positive state dependency in physicians' prescription decisions, indicated by the significant positive effect of the variable "prescriptions dispensed in the last 30 days" on current prescription choice. However, interestingly, we do not find a significant main effect of free samples dispensed in the last 30 days on current prescription choice. What we do find is a significant positive effect for free samples dispensed to new patients. In other words, the higher percentage of free samples dispensed in the past 30 days that were given to new patients, the more likely the physician would prescribe the same brand in the future. We also find that if more of these free samples were provided to patients with no insurance coverage in the past 30 days, it would have a negative effect on current prescription decisions, although the effect is not statistically significant. These results are consistent with our earlier discussion that experimentation via samples will help generate trials and thus lead to increased future sales of the drug, while subsidy in the form of free samples may cannibalize future sales.

While Table 5 presents the overall effect of each incorporated variable by presenting the population-level mean estimates, we also obtain individual-level parameter estimates for each physician using the hierarchical Bayesian approach. These individual-level estimates can help us study the variations of the effectiveness of these two roles across physicians. Figure 1 plots the histograms of the individual-level parameters in the prescription-choice model for parameters associated with the insurance-coverage dummy and the new-diagnosis dummy. Figure 1(a) is for the PPI category. These plots show that, the majority of physicians are more likely to provide free

samples to patients without any insurance coverage and newly diagnosed patients, demonstrating the existence of the dual roles at the individual level. The difference lies in the prevalence of each role among the 770 physicians in our sample. We find only one physician has a negative coefficient[13] on the insurance dummy, while 46 physicians have negative coefficients on the new-diagnosis dummy. This indicates the experimentation role of drug sampling is not as prevalent as the subsidy role among these physicians. Furthermore, comparing the two plots in Figure 1(a), we can see that the parameters for the new-diagnosis dummy (second plot) are more spread among the physicians than the one for the insurance dummy (first plot). This indicates that the effect size of the experimentation role of drug samples varies more among the physicians relative to the subsidy role.

[Insert Figure 1 around here]

In addition, we enriched the physician-level demographic information by matching it with the census data through the zip code each physician practices in.[14] A regression of physician-level parameters on these zip-code–level demographic variables indicates that in the area with a higher proportion of population under the poverty line, physicians are more likely to dispense drug samples to patients without any insurance coverage, as compared to physicians in other areas. This could be due to two reasons: (i) Pharmaceutical firms tend to provide more samples to physicians in these areas and (ii) physicians in the more frugal areas are more likely to provide free samples to patients without any insurance coverage. Both reasons support the subsidy role of samples, which is practiced by either the firm or the physician.

Next we present the estimates of the quantity model for the PPI category in Table 6. These

[13] Not statistically significant.
[14] Due to privacy concerns, the only demographic information we have about each physician is the zip code.

results help us address the question, "Which patients receive more samples conditional on physicians' brand–mode choice?" We find that patients' insurance coverage influences the quantity of free samples they receive from their physicians. In particular, patients without any insurance coverage tend to receive a larger quantity of free samples than patients who have a HMO, PPO, or POS insurance plan, while there is no such statistically significant difference in sample quantity received between patients with Medicare or Medicaid and patients with a HMO, PPO, or POS insurance plan. This finding again suggests a subsidy role played by free samples in physicians' prescription decisions. We also find that new patients and returning patients receiving new treatments tend to receive a lower quantity of free samples relative to revisiting patients who are not changing their treatments. This result provides additional evidence for the experimentation role of free samples: When there is a higher diagnostic uncertainty because the drug is new to the patient, the physician tends to use a small quantity of samples to experiment with the patient. In addition, we find that patient request has a significant negative effect on sample quantity received, while we do not find any significant effect associated with patient race.

[Insert Table 6 around here]

The estimation results of the detailing model are presented in Table 7. Firms in the PPI category in general tend to pay more detailing visits to physicians who have higher intrinsic preference (as represented by higher intercept in the prescription model) towards their own brand, and physicians who are more responsive to their detailing visits (as represented by the higher response parameters in the prescription model). The results also show that firms tend to have some consistency in their detailing decisions over time at the individual-physician level, as indicated by the positive parameter estimates associated with the lagged detailing visits.

[Insert Table 7 around here]

5.2. Results from the ED Category

To assess whether the key qualitative results are specific to the category under study, we conduct an identical empirical analysis using the physician panel data in the ED category. In contrast to most of the prescription-drug categories (including the PPI drugs), which treat essential health problems that are painful or life threatening, ED drugs treat a lifestyle-related health problem.

The estimation results for the choice and quantity models using data from the ED category are reported in the rightmost column in Tables 5 and 6, next to the results for the PPI category. The findings are qualitatively quite similar to those of the PPI category. We find that new patients and returning patients receiving new treatments are more likely to receive free samples from their physicians, and when they do get free samples, they tend to receive a smaller quantity of them compared to other patients who receive free samples. These results are consistent with the experimentation function facilitated by free samples. We also find that patients' insurance coverage tends to play a role in physicians' sample-dispensing decisions, implying free samples serve to subsidize financially indigent patients. In particular, patients without insurance are more likely to receive free samples than patients with some insurance coverage. However, in contrast to what we find in the PPI category, we do not find a significant effect of insurance coverage on the quantity dispensed to a patient as samples in the ED category. We suspect that the different findings could be due to the nature of the therapeutic categories. As the ED drugs treat a lifestyle-related health problem (in other words, generally regarded as a less critical or urgent health problem), physicians are less generous when handing out free samples to patients without insurance coverage.

The above discussion demonstrates the similarities between the findings from the two categories at the population level. Next, we compare the individual-level estimates across the two categories. Figure 1(b) plots the histograms of the individual-level parameters for patient characteristics of no insurance and new diagnosis, the difference between these two plots are very similar to that between those two in Figure 1(a) for the PPI category. That is, the histogram of the parameters for no insurance is much more concentrated than that for new diagnosis. However, there are more negative values for the no insurance parameters in the ED category than the PPI category, but none of them are statistically significant.

5.3. Managerial Implications

The estimation results we reported in previous subsections offer evidence for the existence of drug samples' dual roles, experimental and subsidy, in influencing physicians' prescription decisions. In the current subsection, we carry out several exercises based on the model estimates to demonstrate the magnitude of the effects related to the dual roles. We then discuss the implications of these findings for pharmaceutical managers, patients, and policymakers.

How important are the experimentation role and the subsidy role in physicians' sample dispensing decisions? Suppose a physician treats a representative patient with the following characteristics: Caucasian, with moderate severity, covered by HMO, has visited the physician before for the same condition, and has not requested any particular drug.[15] To quantify the importance of the dual roles, we calculate the relative change in the probability of dispensing free samples when some characteristics of this representative patient change. We find that, everything else being equal, physicians are on average 6.5 times more likely to dispense free samples to a new patient than to this representative patient and 5 times more likely to dispense free samples to a

[15] The characteristics of the representative patient reflect the median values in our data.

patient without any insurance coverage relative to the representative patient. When a new patient does not have any insurance coverage, her chance of receiving free samples is even greater: she is on average 18 times more likely to receive free samples relative to the representative patient. We conduct the same analysis for the ED drugs and obtain very similar results, with slightly lower effects. In summary, being a new patient or a patient without any insurance coverage, or both, could drastically increase the patient's chance of receiving free samples from physicians, reflecting the importance of the dual roles in physicians' sample-dispensing decisions.

We extended the above exercises to evaluate the magnitude of the effect of previous sampling decisions on current prescription decisions. As discussed in an earlier subsection, our estimation results show that the higher the portion of free samples dispensed to new patients in the past 30 days, the higher the probability of the same drug being prescribed at the current patient visit. Therefore, we created two hypothetical scenarios, which differ in the allocation of free samples to new patients. In the first scenario, we assume none of the samples dispensed in the past 30 days were provided to new patients; in the second scenario, we assume these samples were all given to new patients. We calculate the changes in the probabilities between these two scenarios, for the representative patient. The results are listed in the first row of Table 8. The changes in the prescription probabilities are all positive, although rather small in the range of 0.06%–0.16% across the four brands. We then repeated the same exercise, calculated, and report in Table 8 the changes in the prescription probabilities under the condition when the new patient status and the insurance coverage of this representative patient change. Comparing the results across rows, we find that everything else being equal, the changes are most pronounced for a new patient, in the range of 0.36%–0.89% across the four brands. Comparing the results across columns, we can see that the impact on Nexium is the highest, followed by Prevacid, Protonix, and then Aciphex. These

results indicate that among the four brands, Nexium would benefit the most if the company could encourage physicians to dispense a higher proportion of samples to new patients, as its future prescriptions are expected to receive the highest boost.

[Insert Table 8 around here]

Our findings have important implications to pharmaceutical companies' managers, patients, and public policymakers. First, for the pharmaceutical companies, it is beneficial to encourage physicians to conduct mini-trials of their drugs using free samples, because it is likely to lead to more prescriptions in the future. Second, although it may not convert to future sales, dispensing free samples to people with no insurance increases the social welfare and therefore is claimed by the pharmaceutical industry as an important public function it serves the whole society. To efficiently fulfill this function, the current challenge faced by pharmaceutical companies is to figure out other means rather than relying on physicians alone to distribute drug samples so that access to medical care does not become a barrier that prevents the most indigent people from receiving drug samples. This is probably one of the main reasons that many pharmaceutical companies start to develop patients assistance programs targeted to patients who cannot afford to buy the prescriptions. To name a couple, AstraZeneca's Patient and Prescription Assistance Program[16] and Wyeth's Patient Assistance Program[17] are good examples of the initial steps pharmaceutical companies are taking in this initiative.

For patients, one of the central issues concerning their welfare is the long-term financial consequence of using free samples (Chimonas and Kassirer 2009). Drug samples are sometimes

[16] http://www.astrazeneca-us.com/help-affording-your-medicines/

[17] http://www.wyeth.com/contact?rid=/wyeth_html/home/shared/footer/Patient/contact_patient_assist.html Accessed on December 23, 2009.

provided to indigent patients as a subsidy. However, these free samples might do more harm than good to these patients if they must discontinue the treatment after they run out of samples because they cannot afford it. In our paper, we do not find evidence that the use of drug samples by indigent patients, those without any insurance coverage, increases regular prescriptions for the sampled drug in the future. This could be due to the persistent subsidy that physicians provide for these patients or the discontinuity of their treatment by switching to cheaper alternatives. It is worthwhile to conduct further analysis on a matching patient panel to provide a more in-depth account for the long-run consequence of drug-sample use at the individual-patient level.

To public policymakers, one of the main implications of our research is that subsidizing the poor is indeed one of the major motivations underlying physicians' sample-dispensing decisions. Based on our model estimates, we have shown that a patient without any insurance coverage is on average five times more likely than an insured patient to receive drug samples, with everything else held equal. This ratio would further increase to 18 when this uninsured patient also happened to be a new patient. Considering this important public function served by drug samples, it might not be a socially beneficial solution if public policymakers ordered a complete ban of pharmaceutical companies' sampling practices. Programs and measures that encourage pharmaceutical companies to make free medication more accessible to indigent patients might be better solutions. For example, a program offering incentives to establish various sorts of patient-assistance programs may efficiently direct the flow of free samples to the patient population most need of them.

6. Conclusions and Future Research

This study explores the underlying drivers of physicians' free-drug-dispensing decisions

and how current sample dispensing impacts physicians' future prescriptions. Specifically, we conceptualize drug samples' dual roles, experimentation and subsidy, in physicians' prescription decision making, empirically test for the existence of these dual roles, and quantify their long-run sales impact in two therapeutic categories.

In this study, we develop an integrated model for the joint brand choice and sample-dispensing decision and prescription-quantity decision at the individual-physician level in a hierarchical Bayesian framework, and estimate the model with a unique panel data containing detailed information on physicians' sample-dispensing behavior. Our model provides a way to quantify the two roles free samples play in physicians' prescription decisions, (i) the role of subsidy to the poor and (ii) the role of experimenting with patients who have not used the drug before. We find that while both roles are prevalent, the experimenting role sees more variation across physicians. We also find different long-term implications for these two roles. While sampling to new patients stimulates future prescriptions, subsidizing the poor does not.

Our study contributes to both the literature on pharmaceutical marketing and the literature on sampling. To our knowledge, this is the first study in the literature of pharmaceutical marketing to formally define the subsidy and experimentation roles of drug samples and provide empirical evidence (i) supporting the existence and quantifying the magnitude of these dual roles and (ii) quantifying the long-term effect of drug samples on future prescriptions using behavioral data. Such new evidence has the potential to stimulate more theoretical and empirical research regarding the optimal sampling strategy, a heavily employed yet less-understood promotional activity in the pharmaceutical market. This study also contributes to the literature on sampling, which traditionally has focused primarily on product-purchase contexts where consumers decide on both the sample trial and the subsequent product-purchase decisions. Our research proposes and

illustrates how samples function in a different type of market, where consumers must rely on third parties to make these two decisions for them.

Our paper is among the first to offer an understanding of the roles and influence of drug samples on individual physicians' prescription decisions. Nonetheless, many questions regarding drug samples are still unanswered. One of the key limitations in our paper, driven mainly by data availability, is that we do not model the impact of sample inventory on physicians' sample-dispensing decisions. With information on the quantity and frequency of sample dropping at the individual-physician level, future research can examine the effect of this important factor. Second, although we have rich information about a physician panel, we do not have any information about a patient panel. A patient panel combined with the physician panel, could help to study physicians' two uses for drug samples in much more detail at the level of the individual physician–patient pair. Lastly, as we noted in the previous section, the long-term financial consequence of using free samples is one of the central issues concerning patients. With the availability of patient-payment data, future research can investigate the overall cost of treatment associated with free-sample use. The findings of such research can provide us a fuller picture of the overall benefits of free samples on patients and also generate important insights for the health insurance companies in their pricing and insurance-plan design.

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Table 1(a) Free-Sample, and Prescription Shares for Each Brand: PPI

		Conditional on brand choice	
Drug	Brand Share	Share of free samples	Share of prescriptions
Aciphex	19.0%	35.3%	64.7%
Nexium	35.5%	15.8%	84.2%
Prevacid	28.2%	20.8%	79.2%
Protonix	17.3%	25.1%	74.9%
All brands	100%	22.5%	77.5%

Table 1(b) Free-Sample, and Prescription Shares for Each Brand: ED

		Conditional on brand choice	
Drug	Brand Share	Share of Free Samples	Share of Prescriptions
Cialis	31.4%	40.1%	59.9%
Levitra	23.3%	46.0%	54.0%
Viagra	45.3%	34.2%	65.8%
All brands	100%	38.8%	61.2%

Table 2(a) Mean and Standard Deviations of Prescribed Quantity by Each Treatment Mode and Brand: PPI

	Sample only		Prescription	
Brand	Mean	Standard deviation	Mean	Standard deviation
Aciphex	20.5	11.2	40.1	24.3
Nexium	20.0	9.7	43.5	28.0
Prevacid	20.6	12.1	41.0	26.7
Protonix	21.3	10.9	40.0	28.6
All brands	20.6	11.1	41.7	27.2

Table 2(b) Mean and Standard Deviations of Prescribed Quantity by Each Treatment Mode and Brand: ED

	Sample only		Prescription	
Brand	Mean	Standard deviation	Mean	Standard deviation
Cialis	6.03	5.97	16.98	19.06
Levitra	5.88	5.38	17.51	18.10
Viagra	8.03	6.34	16.79	17.37
All brands	6.60	5.93	17.48	18.55

Table 3 Summary Statistics of Patient Characteristics

Patient characteristic	PPI		ED	
	Count	Percentage	Count	Percentage
Ethnicity				
African American	2,563	9.9%	1,695	16.4%
Hispanic	1,898	7.4%	688	6.7%
Caucasian	20,515	79.5%	7,711	74.8%
Other	840	3.2%	215	2.1%
Insurance coverage				
Medicare	2,955	11.5%	1,938	18.8%
Medicaid	1,323	5.1%	317	3.1%
HMO/PPO/POS or other insurance plan	21,300	80.0%	7,608	73.8%
No Coverage (cash only + no insurance)	868	3.4%	446	4.3%
Disease severity status				
Mild or moderate	24,002	93.0%	10,059	97.6%
Severe	1,814	7.0%	250	2.4%
Patient treatment history				
New diagnosis	9,258	35.9%	3,604	35.0%
Returning patient, new treatment	3,416	13.2%	2,323	22.5%
Returning patient	13,142	50.9%	4,382	42.5%
Patient request				
No request	24,465	94.8%	8,326	80.8%
Request for a specific brand	1,351	5.2%	1,983	19.2%

Table 4 Count and Share of Detailing Visits by Each Brand

Table 4(a) PPI

Brand	Count	Share
Aciphex	3,571	22.3%
Nexium	5,028	31.3%
Prevacid	3,860	24.1%
Protonix	3,590	22.4%

Table 4(b) ED

Brand	Count	Share
Cialis	4,070	32.4%
Levitra	4,781	38.0%
Viagra	3,718	29.6%

Table 5 Mean Estimates of the Individual-Level Parameters for the Brand-Mode Choice Model

		PPI		ED
Sample mode				
Brand intercept	Aciphex	0	Cialis	0
	Nexium	–0.46 (–0.55, –0.37)	Levitra	–0.25 (–0.36, –0.13)
	Prevacid	–0.45 (–0.56, –0.34)	Viagra	0.23 (0.13, 0.33)
	Protonix	–0.92 (–1.11, –0.76)		
Detailing stock		0.078 (–0.04, 0.20)		0.13 (0.04, 0.17)
Patient characteristics				
Insurance: comparing to HMO/PPO/POS	Medicare	0.28 (0.18, 0.39)		0.59 (0.49. 0.69)
	Medicaid	–0.27 (–0.46, –0.07)		0.24 (0.05, 0.48)
	No insurance coverage	2.06 (2.22, 2.46)		0.87 (0.64, 1.12)
Race: comparing to Caucasian	African-American	–0.068 (–0.27, 0.12)		0.083 (–0.05, 0.24)
	Hispanic	–0.68 (–0.18. 0.10)		–0.48 (–0.64, –0.30)
Patient status	New patient	2.34 (2.22, 2.46)		2.38 (2.16, 2.62)
	Returning patients with new treatment	2.05 (1.89, 2.12)		1.99 (1.82, 2.18)
Patient request		–1.17 (–1.32, –1.01)		–0.031 (–0.16, 0.12)
Severity		–0.91 (–1.15, –0.66)		0.13 (–0.11, 0.42)
Samples dispensed in the last 30 days		0.048 (–0.044, 0.13)		–0.029 (–0.16, 0.12)
Prescription mode				
Brand intercept	Aciphex	2.20 (2.10, 2.28)	Cialis	1.87 (1.73, 2.04)
	Nexium	3.12 (3.04, 3.19)	Levitra	1.43 (1.28, 1.58)
	Prevacid	2.80 (2.72, 2.87)	Viagra	2.52 (2.37, 2.67)
	Protonix	2.29 (2.21, 2.37)		
Detailing stock		0.083 (0.04, 0.13)		0.087 (0.02, 0.15)
Prescriptions dispensed in the past 30 days		0.063 (0.03, 0.10)		0.14 (0.05, 0.17)
Samples dispensed in the past 30 days		0.030 (–0.08, 0.13)		–0.25 (–0.54, 0.11)
Among samples dispensed in the past 30 days				
% of them to new patients		0.13 (0.01, 0.29)		0.36 (0.00, 0.76)
% of them to returning patients with new treatment		–0.13 (–0.4, 0.16)		–0.39 (–1.18, 0.69)
% of them to patients without insurance		–0.03 (–0.28, 0.25)		0.13 (–0.33, 0.51)

Table 6. Mean Estimates of the Individual-Level Parameters for the Quantity Model

		PPI	ED
Sample mode			
Intercept		2.83 (2.78, 2.88)	1.80 (1.73, 1.88)
Insurance: comparing to HMO/PPO/POS	Medicare	0.022 (–0.08, 0.11)	0.011 (–0.08, 0.10)
	Medicaid	–0.079 (–0.23, 0.07)	–0.018 (–0.22, 0.20)
	Without insurance	0.18 (0.05, 0.29)	–0.011 (–0.15, 0.14)
Race: comparing to Caucasian	African American	–0.028 (–0.13, 0.10)	–0.005 (–0.11, 0.10)
	Hispanic	–0.016 (–0.12, 0.09)	0.025 (–0.11, 0.15)
Patient Status	New patient	–0.22 (–0.28, –0.16)	–0.15 (–0.23, –0.07)
	Returning patient with new treatment	–0.14 (–0.21, –0.07)	–0.21 (–0.29, –0.13)
Patient request		–0.0321 (–0.21, –0.07)	0.0087 (–0.07, 0.09)
Severity		–0.018 (–0.13, 0.09)	0.023 (–0.19, 0.24)
Prescription mode			
Intercept		3.70 (3.66, 3.73)	2.64 (2.59, 2.70)
Insurance: comparing to HMO/PPO/POS	Medicare	–0.073 (–0.14, –0.01)	–0.006 (–0.09, 0.08)
	Medicaid	–0.16 (–0.25, –0.06)	–0.17 (–0.38, 0.08)
	Without insurance	–0.17 (–0.32, –0.00)	–0.089 (–0.31, 0.08)
Race: comparing to Caucasian	African American	–0.12 (–0.20, –0.04)	–0.14 (–0.25, –0.01)
	Hispanic	–0.057 (–0.16, 0.04)	–0.044 (–0.20, 0.12)
Patient status	New patient	–0.36 (–0.41, –0.31)	–0.18 (–0.26, –0.10)
	Revisiting patient with new treatment	–0.15 (–0.22, –0.08)	–0.098 (–0.17, –0.02)
Patient request		0.1181 (0.02, 0.22)	–0.0262 (–0.13, 0.08)
Severity		–0.14 (–0.22, –0.06)	0.030 (–0.24, 0.32)

Table 7(a) Estimation Results for the Detailing Model: PPI

	Aciphex	Nexium	Prevacid	Protonix
Intercept	–0.35 (–0.43, –0.27)	–0.80 (–0.87, –0.71)	–0.61 (–0.69, –0.52)	–0.41 (–0.47, –0.35)
Parameters for prescription model intercept	0.26 (0.22, 0.29)	0.36 (0.33, 0.38)	0.31 (0.27, 0.34)	0.27 (0.25, 0.30)
Parameters for prescription model detailing parameter	–0.02 (–0.06, 0.01)	0.56 (0.50, 0.63)	0.38 (0.24, 0.48)	–0.064 (–0.25, 0.06)
$\text{Log}(\text{Detailing}_{t-1})$	0.15 (0.12, 0.19)	0.074 (0.04, 0.10)	0.093 (0.06, 0.13)	0.16 (0.13, 0.19)
$\text{Log}(\text{Competitive Detailing}_{t-1})$	0.061 (0.04, 0.08)	0.072 (0.05, 0.09)	0.039 (0.02, 0.06)	0.061 (0.05, 0.08)

Table 7(b) Estimation Results for the Detailing Model: ED

	Cialis	Levitra	Viagra
Intercept	0.024 (–0.02, 0.07)	0.092 (0.05, 0.12)	0.041 (0.00, 0.08)
Parameters for prescription model intercept	0.078 (0.06, 0.10)	0.076 (0.06, 0.10)	0.046 (0.03, 0.06)
Parameters for prescription model detailing parameter	–0.11 (–0.19, 0.01)	0.44 (0.25, 0.76)	–0.084 (–0.27, 0.29)
$\text{Log}(\text{Detailing}_{t-1})$	0.49 (0.39, 0.60)	0.51 (0.39, 0.57)	0.44 (0.37, 0.50)
$\text{Log}(\text{Competitive Detailing}_{t-1})$	0.02 (–0.05, 0.07)	0.027 (–0.05, 0.11)	0.0045 (–0.05, 0.06)

Table 8. Changes in Prescription Probabilities If All Samples Dispensed in the Past 30 Days Were Given to New Patients

	Aciphex	Nexium	Prevacid	Protonix
Representative patient – The base case	0.06%	0.16%	0.11%	0.06%
Patient w/o any insurance coverage	0.28%	0.78%	0.55%	0.32%
New patient	0.32%	0.89%	0.63%	0.36%
New patient w/o any insurance coverage	0.27%	0.75%	0.53%	0.30%

Figure 1(a) Histogram of Individual-Level Parameters for No Insurance and New Diagnosis: PPI

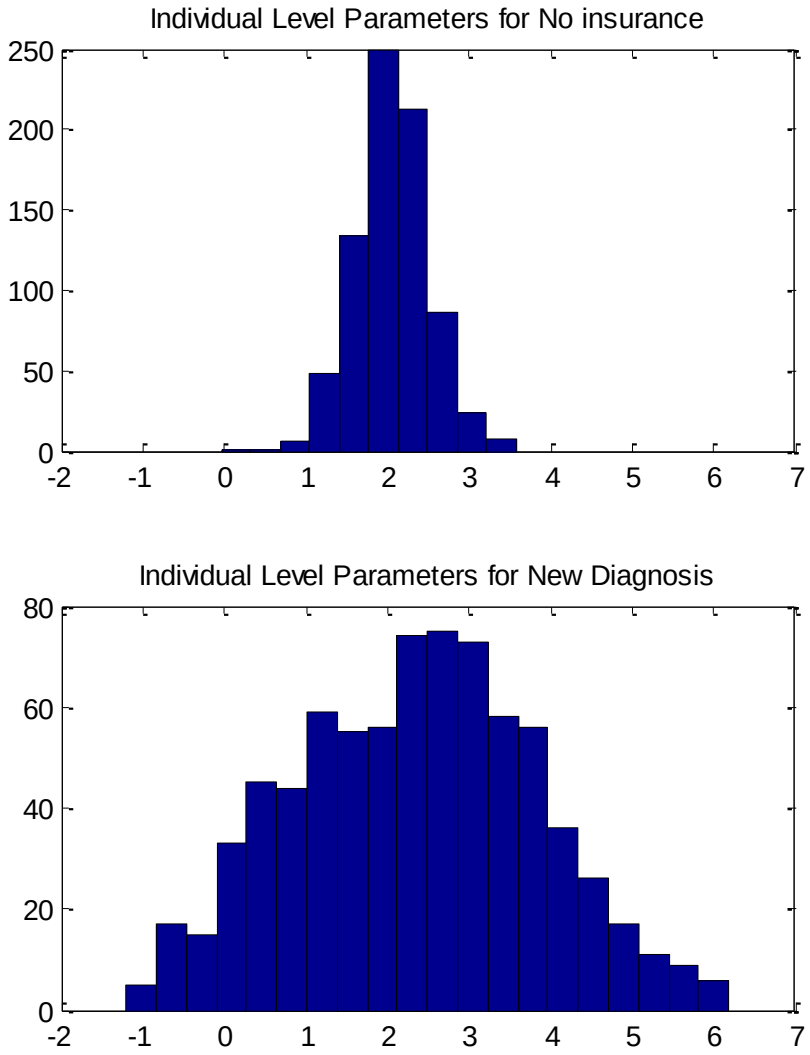

Figure 1(b) Histogram of Individual-Level Parameters for No Insurance and New Diagnosis: ED