NBER WORKING PAPER SERIES

CONSUMER LEARNING AND THE ENTRY OF GENERIC PHARMACEUTICALS

Neha Bairoliya
Pinar Karaca-Mandic
Jeffrey S. McCullough
Amil Petrin

Working Paper 23662
http://www.nber.org/papers/w23662

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2017

We gratefully acknowledge assistance from Amartya Banerjee, Leemore Dafny, Rena Conti, Robin Lee, Sanjog Misra, and Sangwoo Shin. This article benefited from the comments at a number of conferences, including: the American Society of Health Economics (Philadelphia, 2016), Annual Health Econometrics Workshop (Manoa, 2015), Applied Industrial Organization Workshop (Barcelona, 2017), Carribean Health Economics Society Symposium (Virgin Gorda, 2015), and the Midwesten Health Economics Conference (Minneapolis, 2017). We also appreciate the computing resources and technical assistance from the Minnesota Supercomputing Institute as well as the Faculty Research Development Grant from the University of Minnesota Academic Health Center. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w23662.ack

Consumer Learning and the Entry of Generic Pharmaceuticals
Neha Bairoliya, Pinar Karaca-Mandic, Jeffrey S. McCullough, and Amil Petrin
NBER Working Paper No. 23662
August 2017
JEL No. I1

ABSTRACT

Generic pharmaceuticals provide low-cost access to treatment. Despite their chemical equivalence to branded products, many mechanisms may hinder generic substitution. Consumers may be unaware of their equivalence. Firms may influence consumers through advertising or product line extensions. We estimate a structural model of pharmaceutical demand where consumers learn about stochastic match qualities with specific drugs. Naïve models, without consumer heterogeneity and learning, grossly underestimate demand elasticities. Consumer bias against generics critically depends on experience. Advertising and line extensions yield modest increases in branded market shares. These effects are dominated by consumers' initial perception bias against generics.

Neha Bairoliya
Harvard Center for Population and
Development Studies
9 Bow Street
Cambridge, MA 02138
nbairoli@hsph.harvard.edu

Jeffrey S. McCullough
Health Management and Policy
University of Michigan
1415 Washington Heights M3110 SPH II
Ann Arbor, MI 48109
jemccull@umich.edu

Pinar Karaca-Mandic
Division of Health Policy and Management
University of Minnesota
420 Delaware Street SE, MMC 729
Minneapolis, MN 55455
and NBER
pkmandic@umn.edu

Amil Petrin
Department of Economics
University of Minnesota
4-101 Hanson Hall
Minneapolis, MN 55455
and NBER
petrin@umn.edu

1 Introduction

Prescription pharmaceuticals constitute a large and growing share of medical expenditures. Generic products have chemically equivalent active ingredients (i.e., the exact same molecule) and typically yield the same clinical benefits (e.g., Kesselheim et al. (2008), Davit et al. (2009)) at lower prices. Generic entry generally results in lower medical expenditures, increased access, and higher short-run consumer surplus. Consumers usually face strong financial incentives to utilize generics (Duggan et al. (2008), Duggan and Morton (2010), Goedken et al. (2010), Scott Morton and Kyle (2011)). Despite these inducements, generics only constitute about 85% of the prescriptions even a year after the loss of patent exclusivity (Berndt and Aitken, 2011). Researchers and policy makers have argued that increased generic utilization would result in significant cost savings for government programs like Medicare and Medicaid ([Haas et al. (2005), Shrank et al. (2010), Frank (2007) Fischer and Avorn (2004), Rizzo and Zeckhauser (2009)).

Pharmaceutical markets are characterized by uncertainty and heterogeneity (e.g., Bailey (1997), Crawford and Shum (2005), and Ching (2010)). Treatment efficacy and side effects differ across patients and each individual's match with a given drug is initially unknown. Furthermore, initial perceptions may be systematically biased, particularly for generic pharmaceuticals. Patients generally believe that generics are lower quality despite the scientific evidence (Colgan et al. (2015), Greene and Kesselheim (2011)). This may be especially important for patients who initially consumed the branded product.

Pharmaceutical firm strategies may further influence patient perceptions of generic value. Firms may promote their product through direct-to-consumer advertising or physician detailing, thus affecting perceived quality (e.g., Berndt (2005), Iizuka and Jin (2005), Kravitz et al. (2005), Bradford et al. (2006), Sinkinson and Starc (2015)). Pharmaceutical firms may develop follow-on products, often referred to as line extensions. These products may constitute real clinical innovation including formulations that can increase patient compliance or reduce side effects. Line extensions may, however, reduce or delay consumers' adoption of competing generic products (Hemphill and Sampat, 2012). Given the difficulty consumers face in learning about product value, line extensions may effectively differentiate products in excess of any efficacy or side effect differences. This is

particularly important as the line extensions often face later generic entry dates (Shapiro, 2016).[1] These products are employed to effectively extend patent life.

In this article, we address these issues by analyzing the roles of consumer learning and pharmaceutical firm strategies in generic utilization. We estimate a structural model of drug demand that allows for heterogeneity in match quality between consumers and drugs. Furthermore, we allow for marketing activities to influence consumers' prior beliefs about brand quality. In doing so we build on and extend a rich literature on discrete choice demand model [McFadden et al. (1973), Rosen and Small (1979), Trajtenberg (1985), Berry (1994), Petrin (2001)]. Our framework utilizes Bayesian learning models similar to those of Crawford and Shum (2005) and Shin et al. (2012).

We focus on the U.S. oral osteoporosis (OP) drugs from 2007 through 2008. This market includes several branded pharmaceutical products as well as a line extension and a single generic entrant beginning in 2008. The OP market is significant in terms of disease prevalence and pharmaceutical revenues.[2] This sample is also notable as it minimizes two important, and typically unobserved, features in pharmaceutical financing. Pharmaceutical manufacturers sometimes provide coupons to consumers and rebates to both pharmacists and physicians that may undermine incentives from payers (Dafny et al. (2016), Busetzina et al. (2017)). These issues were less prevalent during our study period, are less common for the relatively low cost small-molecule drugs in our sample, and the use of such rebates for Medicare beneficiaries violates federal anti-kickback regulations.

We find wide variation in individual preferences across treatments. These treatment match values encompass both perceived efficacy and side effects. Patients and physicians have little initial knowledge, but most learning occurs within six months of treatment initiation. Models that fail to allow for both heterogeneous match values and learning yield biased parameter estimates and price elasticities. Our estimates suggest that advertising has almost no net effect on generic substitution - this is unsurprising as the branded products almost always cease advertising prior to entry by a generic competitor (Morton (2000)). Line extension products increase demand for branded drugs, but counterfactual experiments suggest that their impact on osteoporosis drug spending is modest

[1]Later generic dates often occur when line extensions are delayed beyond patent expiration when introduced late in a patent period followed by a lengthy FDA approval process. In relatively small product markets line extensions may never face generic competition.

[2]Blume and Curtis (2011) report that roughly 30% of Medicare beneficiaries were treated for either fractures or OP without fractures with an estimated health care cost of $16 billion in the U.S. in 2002.

and they do little to forestall generic substitution. Consumers' individual experiences with branded products has a large influence on demand. Consumers initially perceive generic products to be inferior and only discover their equivalence through experience. These perception biases have a larger and longer-lasting impact on generic substitution and medical expenditure.

The article is organized as follows: In Section 2, we lay out the Bayesian learning model. Section 3 describes our patient-level Medicare claims data set, summary statistics and background on osteoporosis drug market. Section 4 discusses some identification issues. We present the estimation strategy in Section 5 and results are presented in Section 6. Section 7 describes the model fit through in- and out-of-sample predictions. We discuss threats to identification and inference in Section 8. Section 9 presents counterfactual policy simulations and Section 10 provides concluding remarks.

2 Model

Overview

We estimate a structural model of pharmaceutical demand where patients are uncertain about drug match quality, are risk neutral, and myopic. Patients are all newly diagnosed with osteoporosis and have no initial experience with osteoporosis treatments, although they may have initial perceptions regarding product's efficacy or side effects. Perceptions and decisions are formed jointly with physicians, although we simply refer to the patient or consumer for ease of exposition. Initial expectations may be influenced by direct-to-consumer pharmaceutical advertising, physician detailing, as well as unobserved differences in initial ($t = 0$) brand reputations. These initial priors may be particularly imprecise due to the complex nature of medical knowledge and treatment effect heterogeneity. Thus patients and physicians must learn about the match value between each patient and drug. Patients receive match quality signals beginning with the first treatment period ($t = 1$) and update their match quality expectations in a Bayesian manner. In the rest of the section, we lay out the model specification and the assumptions underlying the Bayesian learning model of drug demand.

Utility Function

Consumer i's utility from purchasing pharmaceutical brand j at time t is given by:

$$U_{ij,t} = \beta_{ij,t-1} + \alpha P_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t}, \tag{1}$$

where $\beta_{ij,t}$ denotes patient i's beliefs about the stochastic match quality of drug j at time t. $P_{ij,t}$ is the out-of-pocket price paid by patients for each drug, $X_{ij,t}$ is a vector of other variables related to benefit-design. Finally $\epsilon_{ij,t}$ is a patient-, drug-, and time-specific shock that could include transient changes in wealth or health. Notice that the utility is stochastic because the belief about the match quality is stochastic. The error term $\epsilon_{ij,t}$ is unobserved by the econometrician, but is observable to the patient. We assume that $\epsilon_{ij,t}$ follows *iid* Type I extreme value distribution. The patient is assumed to maximize expected utility given by:

$$U^E_{ij,t} = E[U_{ij,t}] = E[\beta_{ij,t-1}] + \alpha P_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t}. \tag{2}$$

Learning Process

Following the Bayesian learning literature (e.g., Crawford and Shum (2005), Erdem and Keane (1996), Ackerberg (2003), Shin et al. (2012)) we assume that match quality is not revealed in a single instance of drug use. Patients learn about the match quality by updating their beliefs over successive medication utilization experience. More specifically, they receive a noisy signal of match quality after each experience of a particular drug and combine the information contained in the signal with their prior beliefs to obtain posterior beliefs about the drug in accordance with Bayes' rule.

Let $q_{ij,t}$ be the quality signal patient i receives after consuming treatment j at time t. We assume that quality signals follow a normal distribution:

$$q_{ij,t} \sim N(\beta_{ij}, \sigma^2_{q_{ij}}), \tag{3}$$

where β_{ij} is patient i's true match quality for drug j and $\sigma^2_{q_{ij}}$ is the variance of the quality signal.

This implies that learning happens over multiple drug experience occasions and the quality signal is a noisy measure of the true match quality. We further assume that the true match quality is normally distributed in the population:

$$\beta_{ij} \sim MVN(\bar{\beta}, \Omega_{\bar{\beta}}), \tag{4}$$

For identification purposes, we implement a change in variables and formulate this alternate expression for the Bayesian learning process (Shin et al., 2012):

$$\eta_{ij,t} = q_{ij,t} - \beta_{ij} \tag{5}$$

whereas $\eta_{ij,t}$ is the "signal noise" which represents the noise component of the quality signal.

Prior Beliefs

Patients are newly diagnosed with osteoporosis at time $t = 0$ and have no experience with osteoporosis treatment. Patients may, however, form expectations through consultation with physicians, other patients, or pharmaceutical advertising. Patient i's belief about the match quality of drug j at a given time t has the following normal distribution:

$$\beta_{ij,t} \sim N(\mu_{\beta_{ij,t}}, \sigma^2_{\beta_{ij,t}}), \tag{6}$$

where $\mu_{\beta_{ij,t}}$ and $\sigma^2_{\beta_{ij,t}}$ are patient i's beliefs regarding the mean and variance of drug j's match quality at time t. For identification purposes, we define the deviation of patients i's prior belief about the mean quality ($\mu_{\beta_{ij,0}}$) from the true mean quality of the match in the following way:

$$\nu_{ij,0} = \mu_{\beta_{ij,0}} - \beta_{ij} \tag{7}$$

Where we refer to $\nu_{ij,0}$ as the initial "perception bias" of individuals prior to the initiation of treatment (Shin et al., 2012). We allow the initial perception about true match quality of drug to be influenced by pharmaceutical firms' promotional activities. More precisely we allow for consumer

heterogeneity in initial perception bias in the following way:

$$\nu_{ij0} = \bar{\nu_j} + \phi_i(\text{Ad}_{ij} - \frac{1}{N}\sum_i \text{Ad}_{ij}) + \delta_i(\text{Detail}_{ij} - \frac{1}{N}\sum_i \text{Detail}_{ij}) \tag{8}$$

Where Ad_{ij} and Detail_{ij} are aggregate advertising and detailing expenditures respectively by firms for drug j in the month prior to individual i's initiation of treatment. Advertising and detailing are demeaned following the treatment of perception shifters in Shin et al. (2012).

Posterior Beliefs

A patient consuming drug j at time $t = 1$ receives a quality signal and updates beliefs about match quality in a Bayesian manner. Posterior beliefs are normally distributed as the prior at time $t = 0$ and all subsequent signals are normally distributed. Hence the evolution of posterior beliefs can be fully characterized by the laws of motion for posterior mean and variance.

The posterior mean and variance are updated recursively using Bayes' rule:

$$\mu_{\beta_{ij,t}} = \frac{\sigma^2_{\beta_{ij,t}}}{\sigma^2_{\beta_{ij,t-1}}}\mu_{\beta_{ij,t-1}} + d_{ij,t}\frac{\sigma^2_{\beta_{ij,t}}}{\sigma^2_{q_{ij}}}q_{ij,t} \tag{9}$$

$$\sigma^2_{\beta_{ij,t}} = \frac{1}{\frac{1}{\sigma^2_{\beta_{ij,t-1}}} + d_{ij,t}\frac{1}{\sigma^2_{q_{ij}}}} \tag{10}$$

where $d_{ij,t}$ is an indicator variable such that:

$$d_{ij,t} = \begin{cases} 1 & \text{if drug } j \text{ taken in period } t, \\ 0 & \text{otherwise} \end{cases}$$

Iterating forward Equations 9 and 10 yields the following expressions for the match quality mean and variance at time t:

$$\mu_{\beta_{ij,t}} = \frac{\sigma^2_{\beta_{ij,t}}}{\sigma^2_{\beta_{ij,0}}}\mu_{\beta_{ij,0}} + \sum_{\tau=1}^{t} d_{ij,\tau}q_{ij,\tau}\frac{\sigma^2_{\beta_{ij,t}}}{\sigma^2_{q_{ij}}} \tag{11}$$

$$\sigma^2_{\beta_{ij,t}} = \frac{1}{\frac{1}{\sigma^2_{\beta_{ij,0}}} + \frac{\sum_{\tau=1}^{t} d_{ij,\tau}}{\sigma^2_{q_{ij}}}} \tag{12}$$

Using this expression for the evolution of posterior beliefs about the mean match quality of the drug and following the change of variables in Equations 5 and 7 , the expected utility in Equation 2 can be re-written as[3]:

$$U^E_{ij,t} = \beta_{ij} + \nu_{ijt-1} + \alpha P_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t} \tag{13}$$

$$= \beta_{ij} + \frac{\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}}\nu_{ij,0} + \sum_{\tau=1}^{t-1} d_{ij,\tau}\eta_{ij,\tau}}{\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}} + \sum_{\tau=1}^{t-1} d_{ij,\tau}} + \alpha P_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t} \tag{14}$$

Notice that the distributional assumptions on $\epsilon_{ij,t}$ result in a random coefficient multinomial logit model where product-specific intercepts are composed of true mean match quality (β_{ij}) and perception bias ($\nu_{ij,t-1}$).

3 Data

We employ a 5% random sample of Medicare claims data from the Center of Medicare and Medicaid services. The data are constructed using several files, including the 2007-2008 Medicare Part D Prescription Drug Event (PDE) files, Plan Characteristics files, Denominator files, CCW Chronic Conditions Summary files, Medicare Provider Analysis and Review (MedPAR) files, and the Medispan Drug Data Base (MDDB). The PDE files include prescription claims documented by CMS. Denominator files include beneficiaries' demographic information and insurance plan types. MedPAR files provide hospitalization records and disease information through the ICD-9 codes. The CCW Chronic Conditions Summary files contains chronic disease flags and MDDB is a commercial database that provides drug description with National Drug Codes (NDC). These files were merged to create a sample of beneficiaries who were newly diagnosed with osteoporosis and initiated treatment in either 2007 or 2008. Henceforth, we will refer to these two groups as the 2007 cohort and 2008 cohort respectively. We observe prescription drug fills for the 2007 cohort for two years (2007 and 2008). Whereas for the the 2008 cohort, the prescription drug fills are only observed for a single year. Unless otherwise stated the year 2007 and 2008 by themselves will refer only to the

[3]Please refer to Appendix A.3 for further details on these calculations.

calendar periods.

We select a sample of individuals who initiated osteoporosis treatment through first-line oral therapy drugs. An individual is selected if she was observed to have at least one prescription for a drug containing the active ingredients alendronate, ibandronate, risedronate, or raloxifene during the cohort year. We only include those individuals enrolled in traditional fee-for-service Medicare who have stand-alone prescription drug plans. While prescription data is available for Medicare Advantage beneficiaries, we do not observe their outpatient and inpatient claims which are essential for identifying osteoporosis diagnosis and related comorbidities. We also excluded beneficiaries receiving the low-income subsidy as they had no across-drug out-of-pocket price variation, those with chronic conditions that prohibited osteoporosis drug utilization, and those with chronic conditions that are often treated with osteoporosis drugs (see Lin et al. (2014) for a complete list of inclusion restrictions). The resulting sample consisted of 37,435 beneficiary-year observations representing 4,865 unique beneficiaries (2,209 in 2007 cohort and 2,656 in 2008 cohort).

Oral Osteoporosis Drug Market

We focus on FDA approved first-line osteoporosis treatments. These treatments are recommended for newly diagnosed osteoporosis patients. During our study period (2007 - 2008) this market comprises drugs with four active ingredients: alendronate, ibandronate, raloxifene, and risedronate.[4] Alendronate is especially interesting. It was first approved as Fosamax in 1995. In 2005 alendronate was approved in combination with vitamin D_3 as Fosamax Plus D, a line extension of Fosamax. In January of 2008 generic alendronate entered the market. Treatment alternatives such as teriparatide (PTH) injections and non-oral bisphononates exist, but these are not approved for first line therapy and constitute a very small share of the total market during 2007 and 2008.

Choice Set

Our data capture every osteoporosis prescription filled along with the product name, date filled, and the amount supplied. A prescription fill can be of varying lengths, typically 30, 60, or 90 days.

[4] A line extension of Actonel, risedronate sodium plus calcium, was also present during this period but we drop this from our analysis due to it's extremely small market share.

To address this issue, we construct a monthly panel using a 30 days equivalent fill for each of the six drug choices.[5] Table 1 provides the drug choices in our model and their market shares in both 2007 and 2008.[6] Notice that Fosamax had the largest market share in 2007 followed by Actonel. The entry of generic Fosamax in 2008 resulted in a sharp decline in branded Fosamax's market share and only a modest decline in the market share of Actonel.

[Table 1 about here.]

The exclusion of second-line treatments presents a challenge for our choice set. Since injectable treatments such as teriparatide are not observed in our data, we cannot distinguish between patients that forgo treatment altogether from those that transition to second-line. Consequently we normalize choices to Actonel and model demand across second-line treatments. We then consider attrition and censoring in our robustness analyses.

Out-of-Pocket Prices

Prescription drug plans usually include multi-tier formularies that can vary with respect to coinsurance or copayments, coverage in different benefit phases (especially the donut-hole), purchase points etc. Medicare Part-D beneficiaries face complex non-linear cost sharing schedules as they pass through different benefit phases – deductible, pre-initial coverage limit (pre-ICL), gap, and catastrophic coverage. This makes the construction of true out-of-pocket (OOP) prices a challenging task. We follow prior research [Joyce et al. (2002), Karaca-Mandic et al. (2012), Karaca-Mandic et al. (2013)] in constructing out-of-pocket prices for each beneficiary in 2007 and 2008. We use copay/coinsurance information for each plan, it's cost-sharing tier provision, and benefit phase information. Please refer to Appendix A.2 for further detail regarding variable construction. The Medicare Part D pricing structure provides a significant source of out-of-pocket price variation across brands, individuals, and time. We further normalize the out-of-pocket prices by the quantity dispensed and construct a monthly panel using out-of-pocket prices for a 30-days fill. Table 1

[5] A person who has a 60/90 day fill in the data for instance appears as two or three sequential observations in our panel.

[6] Throughout this article, we will present actual/predicted market shares split by calendar years 2007 and 2008 to highlight generic substitution.

provides average out-of-pocket prices for each of the six osteoporosis drugs in the sample for a 30 days fill.

Drug Switches

We observe individuals switch between different drugs over the course of their treatment period. This behavior is informative from an estimation stand point as it helps to understand how idiosyncratic match values are correlated across different drugs. We observe a treatment period of over 12 months for more than 32% of our sample. The evolution of individual market shares over a long treatment period provides a good source of variation to disentangle preference heterogeneity from systematic learning about the match quality of different drugs.

Table 2 provides the switching pattern across various brands. The first column provides the total number of unique switches from a given drug and the second column gives the total number of switches to a given drug. Most of drug switches in our sample are switches to the generic drug when it becomes available; although, a small fraction of of changes switch from the generic to a branded product ($\approx 5\%$).

[Table 2 about here.]

Advertising and Detailing

We use aggregate pharmaceutical detailing and advertising data from IMS and Kantar Media respectively. These data document monthly promotional activities for oral osteoporosis drugs during the years 2007 and 2008. Figure 1 shows the monthly aggregate advertising and detailing expenditures for the branded drugs in our sample. We observe no advertising or detailing expenditures for the generic Fosamax. While detailing expenditures remained relatively stable for Actonel, Boniva, and Evista, they began to plummet for Fosamax and Fosamax Plus D in 2008 with the entry of generic Fosamax. The opposite is true for Evista advertising expenditures which experienced a sharp rise in early 2008.

[Figure 1 about here.]

4 Identification

Intuition for identification

Endogeneity is, of course, a particular concern for demand estimation. Consumers may differ in their unobserved preferences across products and select plans based on out-of-pocket prices; consequently, we focus on newly diagnosed patients. Patients are unlikely to know their preferences prior to treatment initiation and it is unlikely that these factors influenced initial plan selection. These issues could, however, be especially problematic for plan selections made after consumers have begun treatment and learned about their own product-specific preferences. This issue arises during the second year of data for our first cohort. In Section 8 below we test whether informed consumers - those who have experienced treatment prior to play choice - choose plans with lower out-of-pocket prices for purchased products.

We also take advantage of the 2008 generic entry as a quasi-natural experiment. Generic entry provides an exogenous shock to out-of-pocket prices and our estimates include a control for the post-entry period (2008) and a post-entry cohort indicator ($Cohort$). These variables control for unobserved differences across time and cohorts, forming a difference-in-differences identification strategy. Furthermore, we employ data on each individual's out-of-pocket price schedule, constructed using plan and drug-tier information across all of a plan's consumers, rather than out-of-pocket prices of an individual's purchased products. These detailed out-of-pocket price schedule data eliminate a common source of endogeneity in demand estimation.

Under Medicare Part D benefit design, future out-of-pocket prices depend upon current consumption; in particular, prices near the end of the calendar year depend upon consumption in earlier months. Our theoretical model imposes a myopic utility function and ignores these incentives. In our base model, we allow out-of-pocket price elasticity to vary over time by interacting $Price$ with the number of months remaining in the benefits period, $Month$. Although we could not easily estimate more flexible models with Bayesian learning parameters, we explored a variety of simpler (logit demand) models that allowed for parameter heterogeneity as a function of time remaining in the benefit period. These models are discussed in the Robustness Section below and representative results are reported in Appendix B, Tables B.1 and B.2.

Consumer preferences could change with experience. Consumers may, in effect, tire of searching for new products. State-dependent preferences could bias our learning parameters which also change with experience. We re-estimated our *Learning* models while controlling for state-dependence (e.g., the number of previously tried products).

Identification of Bayesian Learning Parameters

The parameters of the Bayesian learning process $\{\beta_{ij}, \sigma^2_{q_{ij}}, \nu_{ij,0}, \sigma^2_{\beta_{ij,0}}\}\ \forall i, j$ are not identifiable in the current form. Identifying assumptions follow Shin et al. (2012). We normalize the quality signal variance $\sigma^2_{q_{ij}}$ to 1 as the initial match quality belief variance $\sigma^2_{\beta_{ij,0}}$ cannot be separately identified from quality signal variance. Their ratio $(\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}})$ can, however, be identified. As mentioned earlier, we allow consumer heterogeneity in initial perception bias but we restrict the ratio of the quality signal variance to the initial match quality belief variance to be homogeneous across consumers such that $\frac{1}{\sigma^2_{\beta_{ij,0}}} = \exp(\kappa)$.

The true mean quality of the drug, β_{ij}, is identified by a patient's steady state drug choices. As the patient receives quality signals over successive drug experiences, learning occurs and the beliefs about match quality evolves to the true match quality. We observe drug choices of patients for up to 24 months following an initial diagnosis. This provides a sufficiently long time series to identify the true mean quality. We normalize one mean quality measure to zero ($\beta_{iJ} = 0$) as not all drug-specific β_{ij}'s are identified. We also normalize the initial perception bias for one product to zero ($\bar{\nu_J} = 0$).

5 Estimation

We estimate parameters of the learning model using the Bayesian method of inference. The set of parameters is given by $\Theta = \{\Phi_i\}_i^N \times \Psi$ where $\Phi_i = \{\beta_{i1}, \ldots, \beta_{iJ-1}, \phi_i, \delta_i, \{\eta_{ij,t}\}_{\tau=1}^{T_i-1}\}$ represents a set of individual-specific parameters and $\Psi = \{\bar{\nu}_1, \ldots, \bar{\nu}_{J-1}, \kappa, \alpha, \gamma\}$ are aggregate level parameters. The likelihood function is defined as:

$$L_i(\mathbf{d_i}|\Phi_i, \Psi) = \prod_{t=1}^{T_i} \prod_{j=1}^{J} \Big(\frac{\exp(\bar{U}^E_{ij,t})}{\sum_{j'} \exp(\bar{U}^E_{ij',t})} \Big)^{d_{ij,t}}.$$

Where:

$$\bar{U}^{E}_{ij,t} = \beta_{ij} + \frac{\exp(\kappa)\nu_{ij,0} + \sum_{\tau=1}^{t-1} d_{ij,\tau}\eta_{ij,\tau}}{\exp(\kappa) + \sum_{\tau=1}^{t-1} d_{ij,\tau}} + \alpha P_{ij,t} + \gamma X_{ij,t}$$

We use a Markov Chain Monte Carlo (MCMC) scheme to draw from the stationary joint posterior density of the parameters. We burn in 1,000,000 iterations to address potential serial correlation based on initial priors. We then use the next 40,000 draws from the joint posterior distribution of the parameter vector for computing the mean values of parameter estimates. Details of the MCMC sampler are provided in Appendix A.1. The MCMC trace and density plots for the posterior means of match qualities are also provided in Appendix B, Figures B.1 and B.2. Finally, we observe that the posterior match quality distributions conform to the assumed multivariate normal distribution (See Appendix B, Figure B.2).

Two additional models are estimated for comparison purposes. We estimate a mixed logit that allows for heterogeneous match values but implicitly assumes these are known to patients and their physicians *ab initio*. We also estimate a conditional logit that effectively assumes match values are known ex ante and identical across patients.

6 Results

We estimate parameters from three alternative demand models. The *Logit* model assumes that match values are homogeneous across patients and known *ex ante*. These models are useful for comparison to much of the pharmaceutical demand literature. We then estimate a *Mixed Logit* model which allows for heterogeneous matches between individual patients and treatments. Finally we estimate a Bayesian learning model that incorporates heterogeneous match values and further allows for patients and physicians to learn about match values over time. Parameter estimates for all three models are reported in Table 3.[7] We label these models as *Logit*, *Mixed Logit*, and *Learning* in Table 3 and in the following text.

The first five rows of Table 3 provide estimates of the out-of-pocket price parameter (α) and

[7]We report the mean of the posterior distribution and 95% credible sets for each parameter of the *Learning* model.

other variables ($X_{ij,t}$) that are common across the three base models. Price elasticities abate slightly over the benefit period ($\gamma_2 > 0$) in all three models. Neither the *Mixed Logit* nor the *Learning* model parameters suggest significant differences before and after generic entry (γ_3) or across cohorts (γ_4). We observe an out-of-pocket price parameter (α) ranging from -0.010 for the *Logit* model to -0.15 for the *Mixed Logit* estimates. These parameters are interpreted in Table 4 and further discussed below.

The second section of Table 3 describes patients' true mean quality. This is the average match value, $\bar{\beta}_j$, for each product relative to Actonel. Patient match value heterogeneities are also reported for the *Mixed Logit* and *Learning* models. The various forms of alendronate sodium (e.g., Fosamax and its generic) have the highest average valuations followed by Actonel (reference good), Boniva, Fosamax Plus D, and Evista respectively. These match values capture a variety of factors including side effects, clinical effectiveness, and institutional features such as automatic generic substitution. We allow the 2007 and 2008 cohorts to have different preferences (β_1 and β_2) over the generic product as these cohorts would likely have different initial experiences with the generic. The *Mixed Logit* model finds large differences in mean match values across the 2007 and 2008 cohorts (0.30 and 9.22 respectively). The *Logit* model generic match values are closer to each other, but the 2008 cohort generic preference parameter (1.99) is still more than double the 2007 cohort preference parameter (0.88). The *Learning* model, however, provides a notably different insight into consumers' valuation of generic pharmaceuticals. Consumers' initially perceptions of generic products (υ_1 and υ_2) are negative, suggesting that they perceive generics to be inferior treatments. This result is particularly large for the 2007 cohort ($\upsilon_1 = -6.58$), although the 2008 cohort's initial perceptions are also biased ($\upsilon_2 = -1.93$). Consumers can, however, learn about their true valuations through experience. We find that the 2007 and 2008 cohorts' true match values (β) - *ex post* learning - are quite similar, 6.09 and 5.85 respectively. For each product we can reject the hypothesis that initial perceptions are unbiased ($\nu_j = 0$ for all j). The *Logit* and *Mixed Logit* estimates are biased as they cannot distinguish the difference between true match values (β) and consumers' initial perception biases (υ).

The heterogeneity terms in the *Mixed Logit* and *Learning* models measure the dispersion of

match values across patients for each product.[8] For each product we can reject the hypothesis that match values are homogeneous and heterogeneity is large relative to the average match value. We further observe that the *Mixed Logit* model generates larger heterogeneity estimates than the *Learning* model.

[Table 3 about here.]

Patients and physicians have little initial knowledge regarding idiosyncratic match values for osteoporosis drugs. Suggesting that these values may only be learned through experience. The third section of Table 3 demonstrates that the initial perception bias, $\nu_{j,0}$, is, quite large on average and initial precision ($\kappa = 0.01$) is quite low. Based on these parameters, we calculate that most consumer learning (and switching) occurs within the six months of treatment experience. Unsurprisingly, both advertising (ϕ) and detailing (δ) improve consumer's initial perceptions of advertised products.

Figure 2 shows the evolution of perception bias across time for each product. This figure reports how biases would evolve over time if the patient consumed a particular drug in every period. More specifically, it plots the term $\frac{\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}}\nu_{ij,0}+\sum_{\tau=1}^{t-1} d_{ij,\tau}\eta_{ij,\tau}}{\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}}+\sum_{\tau=1}^{t-1} d_{ij,\tau}}$ assuming that $d_{ijt} = 1$ every period. There are few things worth mentioning. First, most learning happens fairly quickly, in the first six months. Second, patients from the 2008 cohort learn about generic Fosamax faster than those in the 2007 cohort as they have a smaller initial perception bias. Third, there is no initial heterogeneity in branded drug perception bias ($\nu_{j,0}$) for the generic. This is a consequence of Equation 7 where initial perceptions are constant by drug except for variation due to advertising and detailing and there is no generic advertising or detailing in our data.

[Figure 2 about here.]

Table 4 reports the calculated price elasticities for each product and model. Elasticity estimates differ widely across models. The *Logit* model assumption of homogeneous match values produces downward biased elasticity estimates. Conversely, the *Mixed Logit* model overestimates both consumer heterogeneity (see Table 3) and demand elasticities. Ultimately the *Learning* model suggests that demand is relatively elastic.

[8] Heterogeneity is the posterior mean of the square root of the diagonal element of β_i's variance-covariance matrix $\Omega_{\bar{\beta}}$.

[Table 4 about here.]

Generic elasticities are significantly lower than the elasticities of other products. This may appear counterintuitive, but there are several reasons for this result. All elasticities are normalized to Actonel. Although Actonel's out-of-pocket price is similar to that of other brands, it is more than 300% higher than the generic out-of-pocket price. Consequently a one percent change in any branded price should have a larger effect on demand than a one percent change in the generic price as consumers care about absolute, rather than relative, out-of-pocket prices. Furthermore, competition among generic manufacturers, perception bias, and automatic substitution processes all serve to keep generic prices from rising despite the lower generic demand elasticity.

7 Validation

We estimated the models in Table 3 using data from 70% of the patients in our sample and used data from the remaining 30% to evaluate out-of-sample predictive accuracy. We compare the predicted and actual market shares for each product over time using results from the *Learning* model in Table 3. In Figures 3a and 3b we demonstrate a close match in market shares for the estimation and validation samples with mean squared errors of 0.0026 and 0.05 respectively. Our specification does, however, slightly understate the speed with which generic substitution occurs in 2008. In Figure 3a the actual generic market share exceeds the predicted market share both in- and out-of-sample.

The model does a good job of predicting individual treatment choices within-sample, where we observe the estimated match values. It is, however, much less accurate when predicting out-of-sample individual treatment choices. Accuracy rates for the estimation and validation samples are 92.3% and 55% respectively. This result is unsurprising as even prescribing physicians have little ex ante information regarding patient-level match values.

[Figure 3 about here.]

8 Robustness

We consider several major threats to the validity and robustness of our empirical models. We begin by exploring potential endogeneity and then discuss more flexible frameworks in terms of time controls and state-dependent preferences. In each case, results from our robustness test support our overall conclusions.[9] Finally, we consider issues of attrition and censoring in our data.

Endogeneity is, of course, a particular concern. While product characteristics are fixed through regulation, out-of-pocket prices could be correlated with unobserved variation in preferences. In particular, informed consumers could select insurance plans where out-of-pocket prices are lower for osteoporosis products generally, or for the products that a consumer prefers. In this case the structure of our sample and Medicare policy work to our advantage. All of our consumers are newly diagnosed with osteoporosis and consumers only have the option of switching plans at the beginning of a calendar year. Thus, patients newly diagnosed in early 2007 cannot act on that information until the beginning of 2008 and those newly diagnosed in 2008 cannot switch plans until 2009 which is after the end of our sample. Although this structure does not eliminate the potential for endogeneity, it does provide a natural test. We compare the out-of-pocket prices of drugs consumed in 2008 for the 2007 and 2008 cohorts. If informed consumers - the 2007 cohort during 2008 - are selecting their plans based on their out-of-pocket prices then they should have lower average out-of-pocket prices in 2008. Table 5 shows that 2008 drug prices are nearly identical for both the informed and uninformed patients. Average out-of-pocket prices are, in fact, slightly higher for informed patients suggesting that plan selection is not a threat to identification.

[Table 5 about here.]

The construction of our price measures also helps mitigate endogeneity. Rather than using simple transaction prices, we calculate the price schedule for each consumer, reflecting their plan's formulary as well as the patient's benefit phase (e.g., deductible, pre-ICL, gap, and catastrophic). This reduces the common influence of consumption choice on price measurement.

[9] Unfortunately, we had difficulty estimating models with more parameters than those reported in Table 3. In some cases specific parameters were not identified and in others the trace plots revealed serial correlation even after 2,000,000 burn-in iterations. This was usually near the maximum allowed run time in our computing environment.

We explored two additional sets of robustness tests to explore issues of myopia and state dependence. First, we explored additional interactions between out-of-pocket prices and benefit duration ($Month$) to further relax the myopia assumption. A wide range of alternative specifications estimated via logistic regression yielded extremely similar parameter estimates and price elasticities. A few representative models are presented in Appendix B. Bayesian versions did not fully converge and are not reported but the results appeared to be consistent with estimates reported in Table 3. Finally, we allowed choices to depend on the number of previously chosen products to allow for state-dependent preferences.

Finally, patients with low match values may be more likely to cease oral osteoporosis treatment and those with high match values might continue treatment following the end of our data in December, 2008. We consider the potential for differential attrition and censoring rates across choices. In the data we observe that attrition rates are similar for most drugs, but they are considerably lower for those consuming generic alendronate. This difference is explained by the relatively late entry of generic alendronate - consumers that ceased oral osteoporosis in 2007 couldn't have chosen the generic. We also estimated hazard models of attrition, but the results were extremely sensitive to specification.

We can say something about the potential direction of bias due to censoring for our Bayesian learning parameters. While attrition is concentrated among individuals with low match values, censoring - treatment through December, 2008 - would occur for those with high match values. Most learning occurs within the first three-to-six months of treatment and relatively few patients try more than two different drugs. Very few individuals experience censoring that substantively influence our match value estimates.

9 Counterfactual Policy Simulations

We conduct several counterfactual simulations to illustrate the roles of advertising, line extensions, and consumer perception biases in the generic substitution process. The following sections discuss them in detail.

No Advertising and Detailing

In the first counterfactual, we consider the consequences of eliminating pharmaceutical firms' advertising and detailing activities. We do this by eliminating the effect of advertising and detailing on the initial perception bias. More formally, we set ν_{ij0} in Equation 8 to $\bar{\nu}$. This effectively lowers consumer's initial perceptions of advertised products.

In Figure 4 we observe predicted market shares based on actual promotional expenditures (solid lines) and counterfactual market shares with no advertising expenditures (dashed lines). Fosamax and Fosamax+D expenditures ceased prior to patent expiration and we see that their effects were both modest and short-lived. The elimination of advertising and detailing has the seemingly counterintuitive effect of slightly reducing the generic market share, by 0.7% (see Appendix Table B.3). This is explained by differences in both substitutability across produces and in the advertising levels. The generic's closest substitute, Fosamax, was heavily promoted in early 2007, but promotional activities ceased prior to generic entry. Consequently, restrictions on advertising and detailing would lower Fosamax's pre-generic market share and shift consumption to competing products such as Fosamax+D and Actonel. This loss in pre-generic entry Fosamax market share outweighs the reduction in branded competitor's advertising post-generic entry. This is consistent with the broader research on advertising and patent expiration (Ellison and Ellison, 2011).

[Figure 4 about here.]

An important caveat to this experiment is that our data include only those who initiate oral osteoporosis treatment. We do not consider the impact of advertising on treatment initiation rates; rather, we focus on switching behavior across products. While this focus is especially relevant for studying generic substitution it does not generalize to the general consequences of advertising and detailing.

Eliminating Line-Extensions

Our next counterfactual eliminates the line extension product Fosamax Plus D from the choice-set. We do this by setting an arbitrarily high out-of-pocket price for this drug. Figure 5 illustrates the consequences of removing Fosamax Plus D from the choice set. Eliminating this product

increased the market shares of all incumbent products. Counterfactual generic market shares were 5.07% higher in 2008 (Appendix Table B.3) than it would have been in the absence of Fosamax Plus D. The generic market share also grew over time as the incremental consumers of non-Fosamax products switched to generics. The net effects of eliminating line extensions on total and out-of-pocket expenditures were a 1% and 1.2% reduction respectively.

[Figure 5 about here.]

Change in Generic Perception Bias

We found that the 2007 cohort's perceptions were significantly more biased against generic than the 2008 cohort. Our final simulation applies the 2008 generic perception bias to the 2007 cohort. More precisely, we change the $\bar{\nu_j}$ of individuals in the 2007 cohort and give them the generic perception bias estimated for the 2008 cohort. Changing this bias increases generic market shares by roughly 26.4% during 2008. This bias, based on initial experience with the branded product, dwarfs the consequences of both advertising and line extensions. Figure 6 shows that these differences are particularly striking during the first few months following generic entry. Generic market shares increased by 27% in 2008. Most of these counterfactual differences occurred during the first half of 2008, a significant difference persisted through the year's end. This change reduced consumers' total out-of-pocket osteoporosis treatment expenditures by 11% and total expenditures (by payers and patients) by 7.8%.

[Figure 6 about here.]

It is important to note that although we have relatively good data on patients' out-of-pocket costs, our measures of the gross drug cost - Paid by Medicare Part D - are upward biased. This is because we do not observe negotiated rebates paid by pharmaceutical manufacturers to payers. These rebates are almost certainly larger for branded products than for generics; thus, the total cost reduction should be viewed as an upper bound. We report these numbers in the conclusion despite the potential bias as we believe they still provide useful context for interpreting the magnitude of our effects.

10 Conclusion

We study demand for generic pharmaceuticals in the presence of consumer uncertainty and heterogeneity. We estimate a structural model of drug demand allowing for heterogeneity in match quality between patients and treatments. This heterogeneity may include both side effects and clinical effectiveness; although, side effect variation should dominate in our analytic sample. Initial perceptions about product quality may be biased and learning about match values occurs through experience.

We find that patients and their prescribing physicians have little initial information regarding match values. Their initial perceptions are biased, especially against generic products. This bias is particularly striking for consumers first exposed to branded products before generic entry. This suggests that experiencing differences in product names, labels, and appearance may play an important role of shaping consumer perceptions of pharmaceutical products. We also find that promotional activities, both advertising and detailing, increase initial perception of product values. Despite initially biased perceptions, consumers learn rapidly through experience. We find that initial perceptions are imprecise and most learning occurs within the first three-to-six months of utilization. This suggests that consumers and their physicians recognize the problems with initial information and respond quickly to patient experiences.

Heterogeneity and learning have important implications for measuring the effect of out-of-pocket prices. Our Bayesian learning model suggests that demand is relatively elastic, about -1.6 on average. We compare our results to logistic and hierarchical logistic models. Both of these models assume match values are known *ab initio* and the logistic model further assumes that match values are homogeneous across patients. We reject these assumptions and find that they have sizable implications for price elasticity estimates. Logistic models suggested relatively inelastic demand, with an average elasticity of about -0.07. Although it is difficult to generalize across different types of drugs and conditions, the logistic restuls are consistent with the larger literature on pharmaceutical demand (Goldman et al., 2007). These findings are also consistent with the broader demand estimation literature, where naïve models often underestimate price elasticities (e.g., Nevo (2000)).

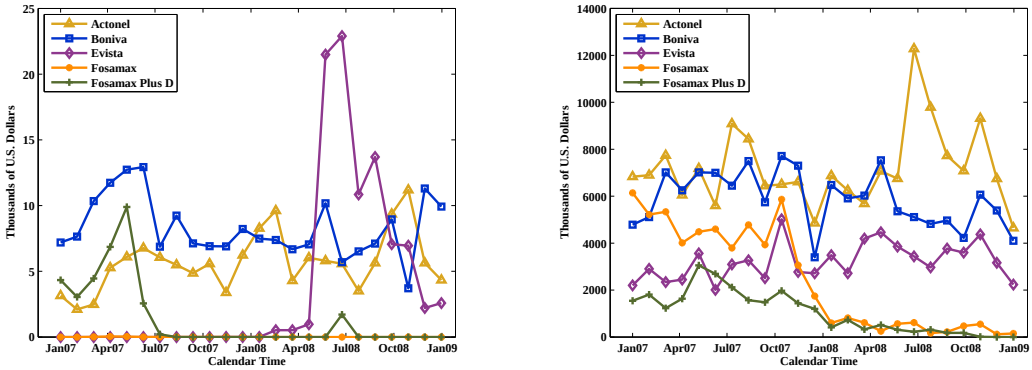
We use our estimates to explore the impact of generic perception bias on pharmaceutical demand. Consumers first exposed to the branded products are particularly biased against generics. Eliminating this bias would greatly accelerate generic substitution, increasing generic market share by an estimated 27% in 2008. This change would reduce total oral osteoporosis expenditures by up to 7.8% and lower consumers' out-of-pocket expenditures by 11%.[10] By comparison we find relatively modest effects from eliminating advertising and line extensions. Eliminating line extensions would increase generic markets shares by 5.1% and had an almost negligible impact on both out-of-pocket and total costs. Unsurprisingly an advertising ban had almost no effect on generic market share. This is because Fosamax ceased advertising prior to generic entry - a common strategy for products with expiring patents.

These results have a number of policy implications. These findings provide further evidence that generics suffer from perception bias and are, ultimately, viewed as high-quality products by informed consumers. There could be a number of mechanisms for increasing generic substitution. State governments and pharmacy board can facilitate, or even mandate, substitution in the absence of a physician order (e.g., Shrank et al. (2010)). Changes in naming and trademark policies could also be used to reduce perception bias (Greene and Kesselheim (2011), Sarpatwari and Kesselheim (2016)). Finally, our results suggest that some studies may understate pharmaceutical demand elasticities, suggesting that patients are more responsive to cost sharing than may often be assumed.

[10] As noted in section 9, the total expenditure reduction is an upper bound and is provided for context.

List of Figures

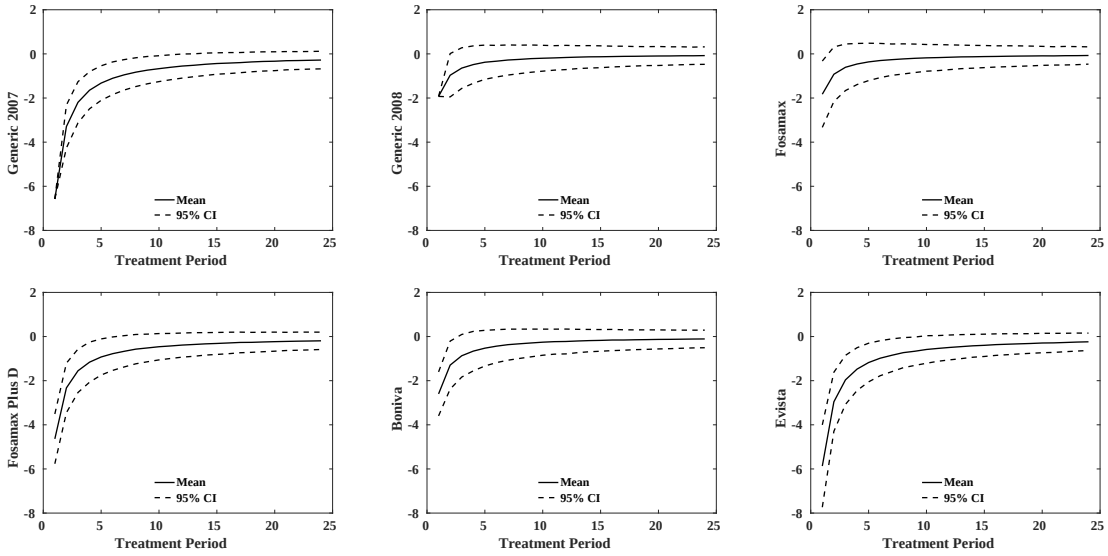
Figure 1: Advertising and Detailing Expenditures



(a) Advertising

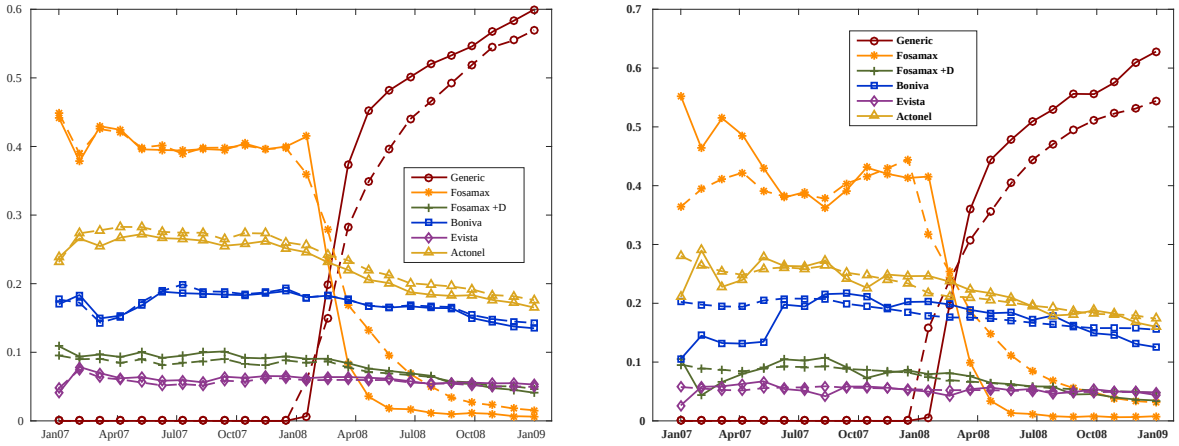
(b) Detailing

Figure 2: Evolution of Perception Bias Over Time



Note: These have been normalized with respect to Actonel

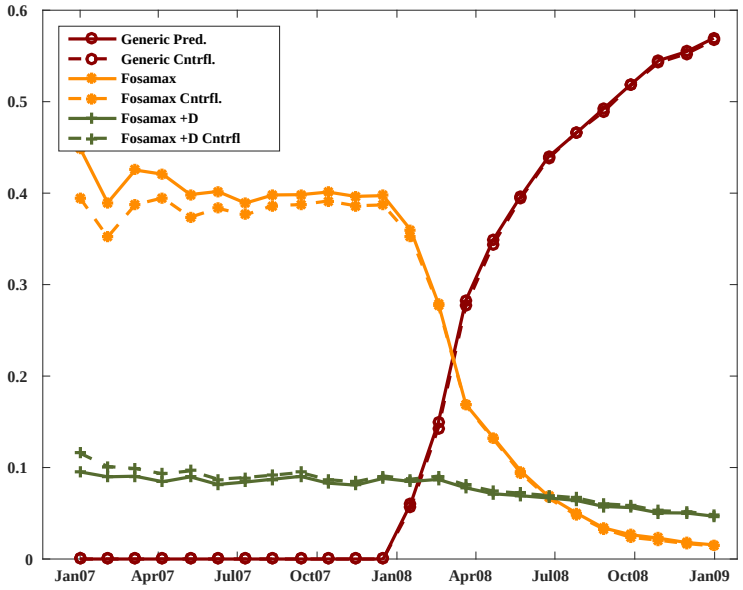
Figure 3: Predicted and Actual Market Shares



(a) Within-Sample (b) Out-Of-Sample

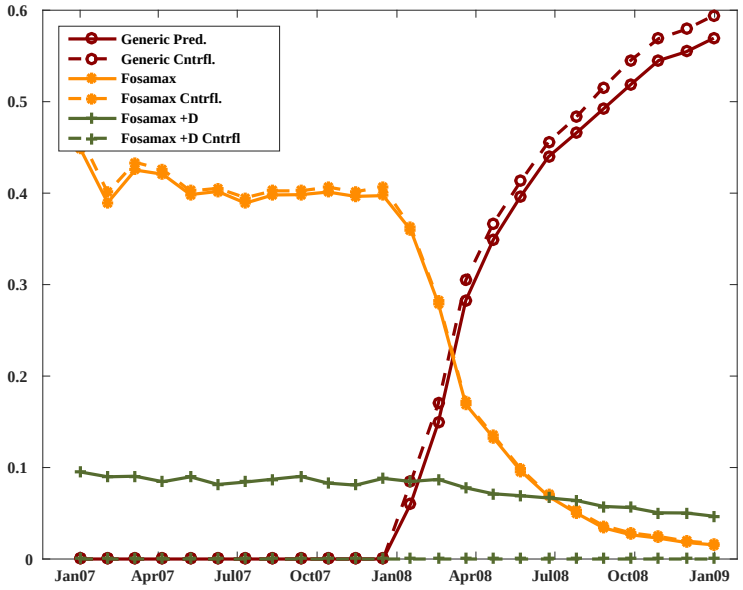
Note: Solid lines indicate actual market shares in the data and dashed lines are predicted market shares based on parameter estimates from the *Learning* model in Table 3. Panel (a) uses data from the estimation sample (70%) and Panel (b) uses data from the validation sample (30%).

Figure 4: Predicted Market Shares by Month:
No Detailing and Advertising in Initial Perception Bias



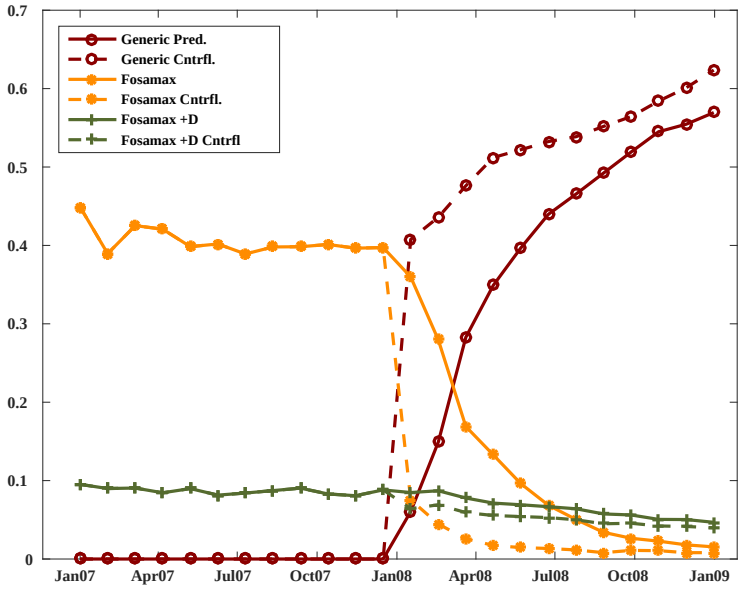
Note: The dased lines indicate predicted market share after the counterfactual and the solid lines indicate predicted market share before the counterfactual.

Figure 5: Predicted Market Shares by Month
Removing Line-Extension from Choice Set



Note: The dased lines indicate predicted market share after the counterfactual and the solid lines indicate predicted market share before the counterfactual.

Figure 6: Predicted Market Shares by Month
Change in Generic Perception Bias for 2007 Cohort



Note: The dased lines indicate predicted market share after the counterfactual and the solid lines indicate predicted market share before the counterfactual.

List of Tables

Table 1: Osteoporosis Drugs, Market Shares and Out-of-Pocket Prices

Product	Active Ingredient	Brand/Generic	Market Share		Price[1]	
			2007	2008	2007	2008
Alendronate	Alendronate	Generic	-	0.47	-	17.51 (15.33)
Fosamax	Alendronate	Brand	0.40	0.05	48.67 (27.80)	60.07 (25.77)
Fosamax+D	Alendronate+D	Brand	0.09	0.06	47.68 (26.31)	48.38 (24.90)
Boniva	Ibandronate	Brand	0.18	0.15	57.65 (24.98)	62.46 (32.13)
Evista	Raloxifene	Brand	0.06	0.05	51.78 (31.50)	56.48 (34.23)
Actonel	Risedronate	Brand	0.26	0.19	51.73 (28.35)	56.14 (30.65)

[1] Mean out-of-pocket prices are reported for a 30 day fill. Standard deviations are reported in parenthesis.

Table 2: Drug Switches

Drug	Switched (from)	Switched (to)
Generic	68	934
Fosamax	773	74
Fosamax+D	106	38
Boniva	152	118
Evista	36	57
Actonel	176	90
Total	1311	1311

Notes: Column 2 in the above table shows the total number of individual switches from a given drug in our sample. Column 3 shows the total number of individual switches to a given drug.

Table 3: Parameter Estimates from Base Models

	Logit		Mixed Logit		Learning Model	
Parameter	Mean	Heterogeneity†	Mean	Heterogeneity†	Mean	Heterogeneity†
P (α)	−0.010 (−0.010,−0.009)		−0.15 (−0.16,−0.14)		−0.08 (−0.10,−0.06)	
Month (γ_1)	−0.065 (−0.071,−0.058)		−0.31 (−1.36,0.74)		1.21 (−0.51,2.93)	
$P *$ Month (γ_2)	0.001 (0.001,0.002)		0.02 (0.02,0.02)		0.01 (0.01,0.01)	
Time Dummy (γ_3)	−0.398 (−0.435,−0.361)		0.36 (−1.17,1.89)		0.39 (−0.71,1.50)	
Cohort Dummy (γ_4)	−0.608 (−0.641,−0.575)		0.39 (−0.85,1.64)		−0.88 (−1.77,0.01)	
True Mean Quality						
Generic, cohort 2007 (β_1)	0.88 (0.83,0.93)	-	0.30 (−0.47,1.08)	10.27 (9.44,11.10)	6.09 (5.62,6.55)	5.89 (5.39,6.40)
Generic, cohort 2008 (β_2)	1.99 (1.94,2.04)	-	9.22 (7.87,10.58)	19.85 (17.36,22.35)	5.85 (5.21,6.50)	9.75 (8.59,10.90)
Fosamax (β_3)	−0.41 (−0.45,−0.37)	-	−2.13 (−2.64,−1.63)	8.87 (8.20,9.53)	−0.37 (−0.67,−0.07)	5.11 (4.74,5.48)
Fosamax Plus D (β_4)	−1.27 (−1.32,−1.22)	-	−30.71 (−36.51,−24.91)	25.84 (21.83,29.85)	−9.04 (−11.42,−6.67)	10.91 (9.17,12.66)
Boniva (β_5)	−0.31 (−0.35,−0.27)	-	−18.42 (−21.92,−14.92)	30.26 (26.04,34.48)	−7.11 (−8.78,−5.45)	14.99 (13.01,16.96)
Evista (β_6)	−1.48 (−1.53,−1.43)	-	−73.86 (−83.91,−63.80)	52.81 (46.46,59.15)	−14.37 (−18.80,−9.93)	14.94 (12.00,17.88)
Initial Perception Bias ν_{ij0}						
Generic, cohort 2007 (ν_1)	-		-		−6.58 (−6.58,−6.58)	
Generic, cohort 2008 (ν_2)	-		-		−1.93 (−1.93,−1.93)	
Fosamax (ν_3)	-		-		−1.83 (−3.33,−0.32)	
Fosamax Plus D (ν_4)	-		-		−4.64 (−5.76,−3.51)	
Boniva (ν_5)	-		-		−2.60 (−3.60,−1.60)	
Evista (ν_6)	-		-		−5.87 (−7.73,−4.00)	
Detail_{ij} - $\overline{\text{Detail}}$ (δ_i)	-	-	-	-	1.33 (1.06,1.59)	0.07 (−0.01,0.16)
Ad_{ij} - $\overline{\text{Ad}}$ (ϕ_i)	-	-	-	-	0.46 (0.22,0.71)	0.94 (−0.16,2.04)
Initial Precision (κ)	-		-		0.01 (0.01,0.01)	
Log-Liklihood	-86390.36		-4648.18		-4236.58	

Notes: Reference group is Actonel. 95 % credible sets for the parameter estimates are reported in brackets.
† Heterogeneity is measured by the standard deviation β_j's posterior distribution.
Time and cohort dummies indicate 2008 calendar year and cohort respectively.
True match values and perception biases are normalized w.r.t. Actonel.

Table 4: Price Elasticities

Product	Logit	Mixed Logit	Learning
Generic	−0.01 (−0.01,−0.00)	−0.39 (−0.46,−0.33)	−0.31 (−0.41,−0.20)
Fosamax	−0.08 (−0.11,−0.06)	−2.76 (−3.08,−2.43)	−1.83 (−2.34,−1.32)
Fosamax Plus D	−0.08 (−0.10,−0.06)	−2.56 (−2.86,−2.26)	−1.71 (−2.18,−1.23)
Boniva	−0.09 (−0.12,−0.07)	−2.80 (−3.14,−2.47)	−1.87 (−2.40,−1.34)
Evista	−0.10 (−0.12,−0.07)	−2.98 (−3.33,−2.63)	−1.98 (−2.54,−1.43)
Actonel	−0.08 (−0.10,−0.06)	−2.52 (−2.81,−2.22)	−1.66 (−2.12,−1.19)

These out-of-pocket price elasticities are based on parameter estimates from Table 3.

Table 5: Mean Out-of-Pocket Drug Prices in 2008 by Cohort

Product	2007 Cohort	2008 Cohort	p-value
Generic	17.95	17.04	0.00
Fosamax	60.47	59.63	0.01
Fosamax+D	48.50	48.24	0.39
Boniva	62.49	62.41	0.83
Evista	56.69	56.25	0.30
Actonel	55.87	56.42	0.14

Notes: Column 2 shows the average out-of-pocket prices paid by the 2007 during 2008. Similarly, column 3 shows the average out-of-pocket prices paid by the 2008 cohort in 2008. Column 4 shows the p-value for the t-test for the difference in the two mean prices.

References

Ackerberg, D. A. (2003). Advertising, learning, and consumer choice in experience good markets: an empirical examination*. *International Economic Review 44*(3), 1007–1040.

Bailey, M. (1997). Comments on berndt, cockburn, griliches, âĂŸpharmaceutical innovations and market dynamics: Tracking effects on price indexes for antidepressant drugsâĂŹ.

Berndt, E. (2005). To inform or persuade? direct-to-consumer advertising of prescription drugs. *New England Journal of Medicine 352*(4), 325–328.

Berndt, E. R. and M. L. Aitken (2011). Brand loyalty, generic entry and price competition in pharmaceuticals in the quarter century after the 1984 waxman hatch legislation. *International Journal of the Economics of Business 18*(2), 177–201.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 242–262.

Blume, S. W. and J. Curtis (2011). Medical costs of osteoporosis in the elderly medicare population. *Osteoporosis International 22*(6), 1835–1844.

Bradford, W. D., A. N. Kleit, P. J. Nietert, T. Steyer, T. McIlWain, and S. Ornstein (2006). How direct-to-consumer television advertising for osteoarthritis drugs affects physicians' prescribing behavior. *Health Affairs 25*(5), 1371–1377.

Busetzina, S., R. M. Conti, N. Yu, and P. B. Bach (2017). Are rebates in part d increasing costs for patients and medicare? *Journal of the American Medical Association: Internal Medicine*.

Ching, A. (2010). Consumer learning and heterogeneity: Dynamics of demand for prescription drugs after patent expiration. *International Journal of Industrial Organization 28*(6), 619–638.

Colgan, S., K. Faasse, L. R. Martin, M. H. Stephens, and A. Grey (2015). Perceptions of generic medication in the general population, doctors and pharmacists: A systematic review. *British Medical Journal*.

Crawford, G. S. and M. Shum (2005). Uncertainty and learning in pharmaceutical demand. *Econometrica 73*(4), 1137–1173.

Dafny, L., C. Ody, and M. Schmitt (2016). When discounts raise costs: the effect of copay coupons on generic utilization.

Davit, B. M., P. E. Nwakama, G. J. Buehler, D. P. Conner, S. H. Haidar, D. T. Patel, Y. Yang, L. X. Yu, and J. Woodcock (2009). Comparing generic and innovator drugs: a review of 12 years of bioequivalence data from the united states food and drug administration. *The Annals of Pharmacotherapy 43*(10), 1583–1597.

Duggan, M., P. Healy, and F. S. Morton (2008). Providing prescription drug coverage to the elderly: America's experiment with medicare part d. *The Journal of Economic Perspectives 22*(4), 69–92.

Duggan, M. and F. S. Morton (2010). The effect of medicare part d on pharmaceutical prices and utilization. *The American Economic Review 100*(1), 590–607.

Ellison, G. and S. F. Ellison (2011). Strategic entry deterrence and the behavior of pharmaceutical incumbents prior to patent expiration. *American Economic Journal: Microeconomics 3*(1), 1–36.

Erdem, T. and M. P. Keane (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing science 15*(1), 1–20.

Fischer, M. A. and J. Avorn (2004). Economic implications of evidence-based prescribing for hypertension: can better care cost less? *Jama 291*(15), 1850–1856.

Frank, R. G. (2007). The ongoing regulation of generic drugs. *New England Journal of Medicine 357*(20), 1993–1996.

Goedken, A. M., J. M. Urmie, K. B. Farris, and W. R. Doucette (2010). Impact of cost sharing on prescription drugs used by medicare beneficiaries. *Research in Social and Administrative Pharmacy 6*(2), 100–109.

Goldman, D., G. Joyce, and Y. Zheng (2007). Prescription drug cost sharing associations with medication and medical utilization and spending and health. *Journal of the American Medical Association 298*(1), 61–69.

Greene, J. A. and A. S. Kesselheim (2011). Why do the same drugs look different? pills, trade dress, and public health. *New England Journal of Medicine 265*(1), 83–89.

Haas, J. S., K. A. Phillips, E. P. Gerstenberger, and A. C. Seger (2005). Potential savings from substituting generic drugs for brand-name drugs: medical expenditure panel survey, 1997–2000. *Annals of internal medicine 142*(11), 891–897.

Hemphill, S. C. and B. N. Sampat (2012). Evergreening, patent challenges, and effective market life in pharmaceuticals. *Journal of Health Economics 31*(2), 327–339.

Iizuka, T. and G. Z. Jin (2005). The effect of prescription drug advertising on doctor visits. *Journal of Economics and Management Strategy 14*(3), 701–727.

Joyce, G. F., J. J. Escarce, M. D. Solomon, and D. P. Goldman (2002). Employer drug benefit plans and spending on prescription drugs. *Jama 288*(14), 1733–1739.

Karaca-Mandic, P., A. B. Jena, G. F. Joyce, and D. P. Goldman (2012). Out-of-pocket medication costs and use of medications and health care services among children with asthma. *JAMA 307*(12), 1284–1291.

Karaca-Mandic, P., T. Swenson, J. M. Abraham, and R. L. Kane (2013). Association of medicare part d medication out-of-pocket costs with utilization of statin medications. *Health Services Research 48*(4), 1311–1333.

Kesselheim, A. S., A. S. Misono, J. L. Lee, M. R. Stedman, A. M. Brookhart, N. K. Choudhry, and W. H. Shrank (2008). Clinical equivalence of generic and brand name drugs used in cardiovascular disease: A systematic review and meta-analysis. *Journal of the American Medical Association 300*(21), 2514–2526.

Kravitz, R. L., R. M. Epstein, M. D. Feldman, C. E. Franz, R. Azari, M. S. Wilkes, L. Hinton, and P. Franks (2005). Influence of patients' requests for direct-to-consumer advertised antidepressants: A randomized controlled trial. *Journal of the American Medical Association 293*(16), 1995–2002.

Lin, C.-W., P. Karaca-Mandic, J. S. McCullough, and L. Weaver (2014). Access to oral osteoporosis drugs among female medicare part d beneficiaries. *Women's Health Issues 24*(4), e435–e445.

McFadden, D. et al. (1973). Conditional logit analysis of qualitative choice behavior.

Morton, F. M. S. (2000). Barriers to entry, brand advertising, and generic entry in the us pharmaceutical industry. *International Journal of Industrial Organization 18*(7), 1085–1104.

Nevo, A. (2000). A practitioners guide to estimation of random-coefficient logit models of demand. *Journal of Economics & Management Strategy 9*(4), 513–548.

Petrin, A. (2001). Quantifying the benefits of new products: The case of the minivan. Technical report, National Bureau of Economic Research.

Rizzo, J. A. and R. Zeckhauser (2009). Generic script share and the price of brand-name drugs: the role of consumer choice. *International journal of health care finance and economics 9*(3), 291–316.

Rosen, H. S. and K. A. Small (1979). Applied welfare economics with discrete choice models.

Sarpatwari, A. and A. S. Kesselheim (2016). The case for reforming drug naming: Should brand name trademark protections expire upon generic entry? *PLos Med 13*(2).

Scott Morton, F. and M. Kyle (2011). Markets for pharmaceutical products. In M. V. Pauly, T. G. McGuire, and P. P. Barros (Eds.), *Handbook of Health Economics*, Volume 2, Chapter 12, pp. 763–823. Elsevier.

Shapiro, B. T. (2016). Estimating the cost of strategic entry delay in pharmaceuticals: The case of ambien cr. *Quantitative Marketing Economics*.

Shin, S., S. Misra, and D. Horsky (2012). Disentangling preferences and learning in brand choice models. *Marketing Science 31*(1), 115–137.

Shrank, W. H., N. K. Choudhry, J. Agnew-Blais, A. D. Federman, J. N. Liberman, J. Liu, A. S. Kesselheim, M. A. Brookhart, and M. A. Fischer (2010). State generic substitution laws can lower drug outlays under medicaid. *Health affairs 29*(7), 1383–1390.

Sinkinson, M. and A. Starc (2015). Ask your doctor? direct-to-consumer advertising of pharmaceuticals.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

Trajtenberg, M. (1985). The welfare analysis of product innovations with an application to ct scanners. Technical report, National Bureau of Economic Research.

A Technical Appendix

A.1 MCMC Sampler

We employ a Bayesian approach to estimate the parameters $\{\beta_{i1}, ..., \beta_{iJ-1}, \phi_i, \delta_i, \{\eta_{ij,t}\}_{\tau=1}^{T_i-1}, \bar{\nu}_1, ..., \bar{\nu}_{J-1}, \kappa, \alpha, \gamma\}$. This requires an unconditional prior distribution of the parameter vector along with the likelihood function.

Prior Distribution

We specify the prior distribution of our parameters as:

$$
\begin{aligned}
[\beta_i|\bar{\beta}, \Omega_{\bar{\beta}}] &\sim MVN(\bar{\beta}, \Omega_{\bar{\beta}}) \\
[\bar{\beta}|\bar{\beta}_0, S_0] \sim MVN(\bar{\beta}_0, S_0) \text{ and } [\Omega_{\bar{\beta}}|K, I] &\sim IW(K, I) \\
[\phi_i|\bar{\phi}, \Omega_{\bar{\phi}}] &\sim MVN(\bar{\phi}, \Omega_{\bar{\phi}}) \\
[\bar{\phi}|\bar{\phi}_0, S_{\phi_0}] \sim MVN(\bar{\phi}_0, S_{\phi_0}) \text{ and } [\Omega_{\bar{\phi}}|m, M] &\sim IW(m, M) \\
[\delta_i|\bar{\delta}, \Omega_{\bar{\delta}}] &\sim MVN(\bar{\delta}, \Omega_{\bar{\delta}}) \\
[\bar{\delta}|\bar{\delta}_0, S_{\delta_0}] \sim MVN(\bar{\delta}_0, S_{\delta_0}) \text{ and } [\Omega_{\bar{\delta}}|n, N] &\sim IW(n, N) \\
[\alpha|\alpha_0^m, \alpha_0^v] &\sim N(\alpha_0^m, \alpha_0^v) \\
[\gamma|\gamma_0^m, \gamma_0^v] &\sim N(\gamma_0^m, \gamma_0^v) \\
[\bar{\nu}|\nu_0^m, \nu_0^v] &\sim MVN(\nu_0^m, \nu_0^v) \\
[\kappa|\sigma_0^m, \sigma_0^v] &\sim N(\sigma_0^m, \sigma_0^v) \\
[\eta_{ij,t}|\mu_\eta, \sigma_\eta] &\sim N(\mu_\eta, \sigma_\eta)
\end{aligned}
$$

The joint prior distribution of our parameter vector $\Theta = \{\Phi_i\}_i^N \times \Psi$ is thus given by:

$$
\begin{aligned}
k(\Theta) = \prod_{i=1}^{N} \Big([\beta_i|\bar{\beta}, \Omega_{\bar{\beta}}][\phi_i|\bar{\phi}, \Omega_{\bar{\phi}}][\delta_i|\bar{\delta}, \Omega_{\bar{\delta}}] \prod_{\tau=1}^{T_i} [\eta_{ij\tau}|\mu_\eta, \sigma_\eta] \Big) \times [\bar{\beta}|\bar{\beta}_0, S_0] \times [\Omega_{\bar{\beta}}|K, I] \times [\alpha|\alpha_0^m, \alpha_0^v] \\
\times [\gamma|\gamma_0^m, \gamma_0^v] \times [\bar{\nu}|\nu_0^m, \nu_0^v] \times [\kappa|\sigma_0^m, \sigma_0^v]
\end{aligned}
$$

Joint Posterior Distribution

Given the prior distribution of the parameter vector and the likelihood function, the joint posterior distribution of the parameter vector conditional on the data is given by:

$$
K(\Theta|\{\mathbf{d_i}\}_{i=}^N) \propto \prod_{i=1}^{N} L_i(\mathbf{d_i}|\Phi_i, \Psi) k(\Theta)
$$

Bayesian inference requires drawing from the joint posterior distribution of the parameter vector. It is possible to directly draw from this distribution using the Metropolis Hastings algorithm, but this is computationally slow. Consequently, draws from this distribution are obtained through Gibbs sampling. This is an iterative process that requires drawing each parameter conditional on other parameters. Following (Train, 2009), we specify the Gibbs sampling procedure for drawing from the joint posterior distribution.

1. Update $\beta_i = \{\beta_{i1}, ..., \beta_{iJ-1}\}$ using a Metropolis-Hastings sampler.

2. Update $\bar{\beta}$ and $\Omega_{\bar{\beta}}$ using a Gibbs sampler.

3. Update ϕ_i using a Metropolis-Hastings sampler.

4. Update $\bar{\phi}$ and $\Omega_{\bar{\phi}}$ using a Gibbs sampler.

5. Update δ_i using a Metropolis-Hastings sampler.

6. Update $\bar{\delta}$ and $\Omega_{\bar{\delta}}$ using a Gibbs sampler.

7. Update α and γ by a Metropolis-Hastings sampler.

8. Update $\{\bar{\nu}_1, ..., \bar{\nu}_{J-1}, \bar{\sigma}^2_{\beta_0}\}$ using a Metropolis-Hastings sampler

9. Update $\{\eta_{ij,\tau}\}_{\tau=1}^{t-1}$ by a Metropolis-Hastings sampler.

A.2 Out-of-Pocket Prices

To construct true out-of-pocket costs for each drug we employed copayment and coinsurance information from the plans for each tier and benefit phase. Encrypted plan and contract identifiers in the Part D denominator files were linked to the PDE files. This identified the plan under which each beneficiary was enrolled in a given time period. Plan Characteristic files provided plan cost sharing and type of tier information: Brand/Preferred Brand (BPB), Non-Preferred Brand (NPB), Generic/Preferred Generic (GPG), Non-Preferred Generic (GPG), and d99 (plans that use a standard 25% coinsurance rate). These were available for both the pre-initial coverage limit (pre-ICL), the benefit phase preceding the donut hole, and Gap phases during the donut hole.

We first constructed the average gross drug costs for each drug covered by the tiers BPB, NPB, GPG, NPG, and d99 under each benefit phase and for each year. For the Deductible and Catastrophic phases, we only constructed the average drug cost by year. In order to construct drug costs by tiers, we merged the plan characteristics data with the PDE files for each year separately. We then coded gap and pre-ICL tiers using information in the plan characteristics files. We then generated mean average gross drug cost for each drug in each of the five tiers as well as the Gap and Pre-ICL phases for the two years.

The primary challenge we faced in constructing out-of-pocket costs for each drug under each plan was that in the 5% Part D sample we do not observe transactions for all relevant osteoporosis drugs in every plan. We employed the following rules to calculate out-of-pocket prices:

- **Rule 1** If a drug is purchased for a given PDE plan then the actual formulary tiers (i.e., copayment and coinsurance rates) are applied to calculate the out-of-pocket cost.

- **Rule 2** If no transactions are occurred for a given drug-plan combination we examined data from other plans with the same contract ID as plans within contract IDs have highly correlated formulary and pricing structures. Using this broader set of data we inferred the formulary tier and applied the appropriate plan-specific coinsurance and copayment rates to calculate out-of-pocket costs.

- **Rule 3** If no transactions are observed for a given drug and contract ID we applied the formulary tier most frequently observed for that drug using data from other contract IDs. We then used the plan's own copayment and coinsurance rate for that formulary tier when calculating out-of-pocket costs.

- **Rule 4** If we see that some drug is covered as NPG/NPB in the population but a particular plan does not have copay/coinsurance information on the NPG/NPB tier, we then use the copay/coinsurance information on GPG/BPB respectively, if available in computing out-of-pocket costs.

A.3 Mathematical Appendix

This section provides the derivation of equation 14. From equations 11 and 12, we have:

$$\mu_{\beta_{ij,t}} = \frac{\sigma^2_{\beta_{ij,t}}}{\sigma^2_{\beta_{ij,0}}}\mu_{\beta_{ij,0}} + \sum_{\tau=1}^{t} d_{ij,\tau} q_{ij,\tau} \frac{\sigma^2_{\beta_{ij,t}}}{\sigma^2_{q_{ij}}} \tag{15}$$

$$\sigma^2_{\beta_{ij,t}} = \frac{1}{\frac{1}{\sigma^2_{\beta_{ij,0}}} + \frac{\sum_{\tau=1}^{t} d_{ij,\tau}}{\sigma^2_{q_{ij}}}} \tag{16}$$

Substituting for the value of $\sigma^2_{\beta_{ij,t}}$ in equation 15 we get:

$$\mu_{\beta_{ij,t}} = \frac{\mu_{\beta_{ij,0}}}{1 + \frac{\sigma^2_{\beta_{ij,0}}}{\sigma^2_{q_{ij}}} \sum_{\tau=1}^{t} d_{ij,\tau}} + \frac{\sum_{\tau=1}^{t} d_{ij,\tau} q_{ij,\tau}}{\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}} + \sum_{\tau=1}^{t} d_{ij,\tau}} \tag{17}$$

Subtracting β_{ij} from both sides of equation 17 and simplifying gives:

$$\mu_{\beta_{ij,t}} - \beta_{ij} = \frac{\mu_{\beta_{ij,0}}\sigma^2_{q_{ij}} + \sigma^2_{\beta_{ij,0}} \sum_{\tau=1}^{t} d_{ij,\tau} q_{ij,\tau} - \beta_{ij}\sigma^2_{q_{ij}} - \beta_{ij}\sigma^2_{\beta_{ij,0}} \sum_{\tau=1}^{t} d_{ij,\tau}}{\sigma^2_{q_{ij}} + \sigma^2_{\beta_{ij,0}} \sum_{\tau=1}^{t} d_{ij,\tau}} \tag{18}$$

Substituting from equations 7 and 5 and simplifying we get:

$$\nu_{ijt-1} = \frac{\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}}\nu_{ij,0} + \sum_{\tau=1}^{t-1} d_{ij,\tau}\eta_{ij,\tau}}{\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}} + \sum_{\tau=1}^{t-1} d_{ij,\tau}} \tag{19}$$

Substituting for ν_{ijt-1} from 19 in equation 13 we get:

$$U^E_{ij,t} = \beta_{ij} + \frac{\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}}\nu_{ij,0} + \sum_{\tau=1}^{t-1} d_{ij,\tau}\eta_{ij,\tau}}{\frac{\sigma^2_{q_{ij}}}{\sigma^2_{\beta_{ij,0}}} + \sum_{\tau=1}^{t-1} d_{ij,\tau}} + \alpha P_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t}$$

B Additional Figures and Tables

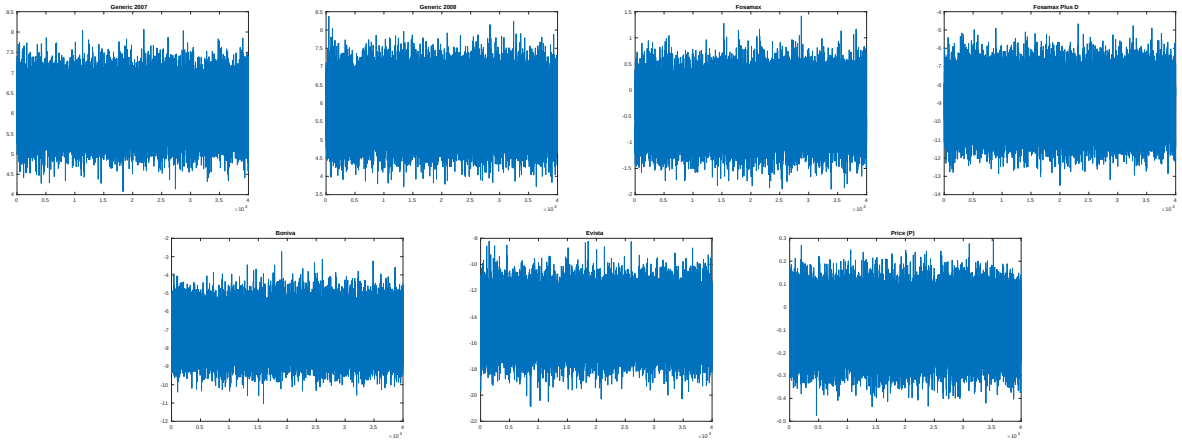
Table B.1: Alternate Logit Specifications:
Price Elasticities

	Benchmark	Model 1	Model 2
Generic	-0.009	-0.006	-0.007
	(-0.013,-0.004)	(-0.010,-0.001)	(-0.012,-0.003)
Fosamax	-0.085	-0.090	-0.089
	(-0.107,-0.062)	(-0.113,-0.068)	(-0.111,-0.067)
Fosamax Plus D	-0.082	-0.085	-0.085
	(-0.103,-0.062)	(-0.106,-0.065)	(-0.105,-0.064)
Boniva	-0.092	-0.098	-0.096
	(-0.115,-0.068)	(-0.122,-0.074)	(-0.120,-0.073)
Evista	-0.099	-0.102	-0.102
	(-0.122,-0.075)	(-0.126,-0.078)	(-0.126,-0.078)
Actonel	-0.084	-0.089	-0.088
	(-0.104,-0.064)	(-0.109,-0.069)	(-0.108,-0.068)

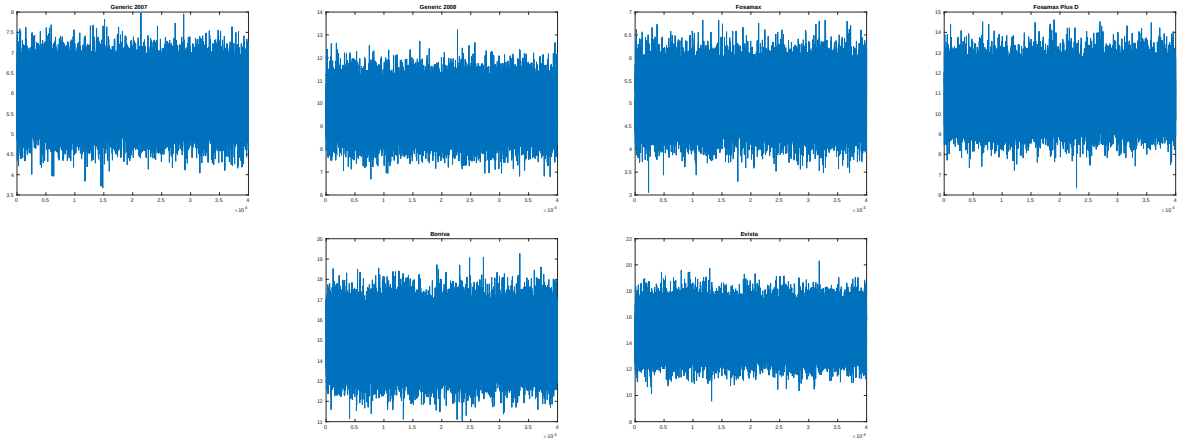
"Benchmark" refers to the *Logit* model in Table 3

Figure B.1: MCMC Trace Plots

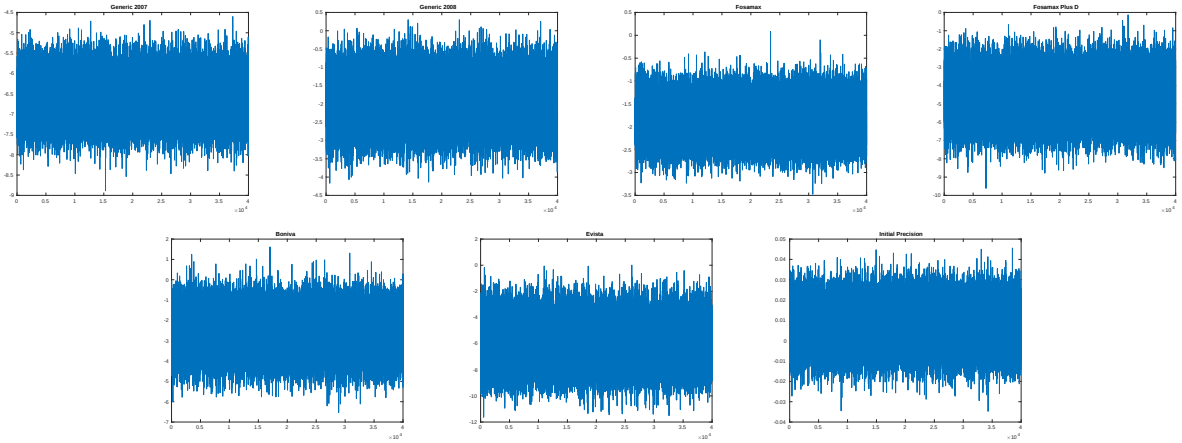
(a) Mean True Match Value and Out-of-Pocket Price



(b) Heterogeneity

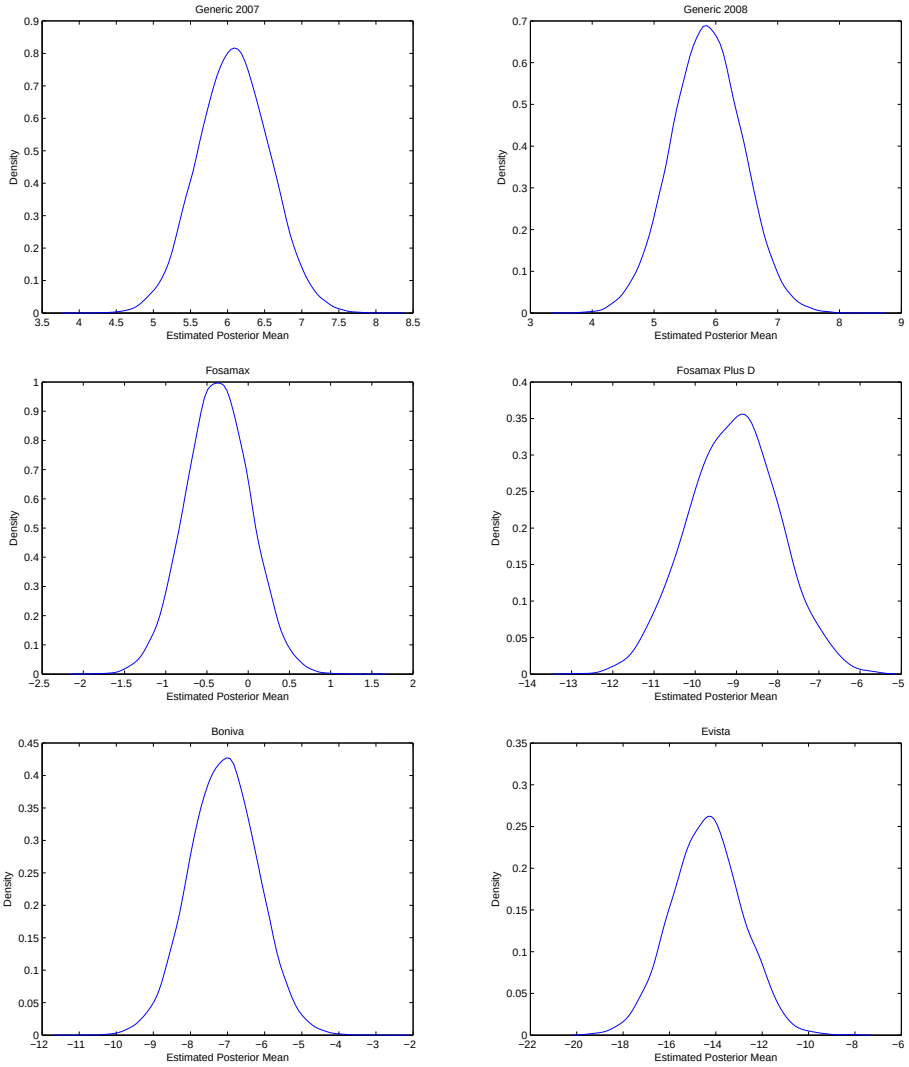


(c) Perception Bias and Precision



Note: The figure shows that after a burn-in of 1 million iterations, the MCMC sampler mixes well which indicates convergence to the true posterior distribution.

Figure B.2: Estimated Posterior Means of True Match Quality



Note: The figure indicates that the estimated posterior density of the match values follows a normal distribution as expected.

Table B.2: Alternate Logit Specifications:
Parameter Estimates

	Benchmark	Model 1	Model 2
Price	-0.010	-0.009	-0.009
	(-0.010,-0.009)	(-0.011,-0.007)	(-0.010,-0.007)
P × X	0.001	0.004	0.002
	(0.001,0.002)	(0.003,0.005)	(0.001,0.002)
P × X^2		-0.001	
		(-0.001,-0.001)	
P × X^3		0.000	
		(0.000,0.000)	
Q_{t_1} × P			-0.002
			(-0.006,0.002)
Q_{t_2} × P			-0.009
			(-0.012,-0.006)
Q_{t_3} × P			-0.005
			(-0.006,-0.003)
X	-0.065	-0.201	-0.089
	(-0.071,-0.058)	(-0.276,-0.126)	(-0.115,-0.062)
X^2		0.046	
		(0.032,0.060)	
X^3		-0.003	
		(-0.004,-0.002)	
Q_{t_1}			0.109
			(-0.133,0.352)
Q_{t_2}			0.401
			(0.234,0.568)
Q_{t_3}			0.215
			(0.118,0.311)
2008 Cohort Dummy	-0.398	-0.388	-0.390
	(-0.435,-0.361)	(-0.425,-0.351)	(-0.427,-0.354)
2008 Year Dummy	-0.608	-0.615	-0.614
	(-0.641,-0.575)	(-0.649,-0.582)	(-0.647,-0.581)
Generic 2007	0.875	0.889	0.884
	(0.826,0.925)	(0.839,0.939)	(0.834,0.934)
Generic 2008	1.991	1.975	1.981
	(1.939,2.043)	(1.923,2.027)	(1.929,2.033)
Fosamax	-0.408	-0.408	-0.408
	(-0.446,-0.370)	(-0.446,-0.370)	(-0.446,-0.370)
Fosamax Plus D	-1.269	-1.271	-1.270
	(-1.316,-1.223)	(-1.318,-1.224)	(-1.317,-1.224)
Boniva	-0.312	-0.313	-0.312
	(-0.349,-0.274)	(-0.350,-0.275)	(-0.350,-0.275)
Evista	-1.482	-1.487	-1.485
	(-1.532,-1.432)	(-1.537,-1.437)	(-1.535,-1.435)
Constant	-0.325	-0.318	-0.358
	(-0.378,-0.272)	(-0.435,-0.202)	(-0.430,-0.287)

"Benchmark" refers to the *Logit* model in Table 3

Table B.3: Changes in Costs and Generic Market Shares: 2008

	Total Cost[1,2] (Mil. $)			OOP Cost[1] (Mil. $)			%Δm.s.[1,3]
	Model	Exp.	%Δ	Model	Exp.	%Δ	
Exp. 1	1895	1899	0.2	904	907	0.3	-0.7
Exp. 2	1895	1875	-1.0	904	893	-1.2	5.1
Exp. 3	1895	1747	-7.8	904	804	-11.1	26.5

[1]The total costs and scripts reported in our sample are scaled by year-specific weights to represent the entire Medicare Part D population undergoing first-line pharmacologic treatment for osteoporosis during 2008.

[2]We use average total drug cost reported in the claims data for the given year in computing the total cost.

[3]Percent change in generic's market share.