Inertia and Learning in Physician Prescribing Behavior

by

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THESIS

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LIST OF ABBREVIATIONS

ACA	Affordable Care Act
AMI	acute myocardial infarction
ANDA	Abbreviated New Drug Application
CCS	Clinical Classification Software
CMS	Centers for Medicare and Medicaid
COPD	chronic obstructive pulmonary disease
DTCA	direct-to-consumer advertising
EHR	electronic health record
FDA	Food and Drug Administration
HMO	health maintenance organization
NDC	National Drug Code
NPI	National Provider Identifier
PBM	pharmacy benefits manager
PPO	preferred provider organization
XR	Extended Release

SUMMARY

This thesis uses multiple econometric techniques to study physician prescribing behavior following generic entry. Pharmaceutical spending in the United States is high and there is a vigorous policy debate on lowering prescription drug spending, focused on increasing the use of low-cost generics. However, the switch to generic drugs once they become available occurs slowly and is costly to both patients and insurers. It is therefore important to understand why slow generic uptake occurs in order to develop policies that can curb high pharmaceutical spending.

The first chapter introduces the research question and provides background on the setting and data. The second chapter exploits variation in when physicians begin prescribing to use a quasi-experimental approach. This chapter shows that physicians familiar with the drug class before generic entry are more likely to prescribe the brand-name drug after generic entry, showing that inertia toward the brand-name drug exists.

In the third chapter, a structural model of physician demand for atypical antipsychotics is used to identify mechanisms—switching costs and learning—of physician inertia in prescribing. Results show that physicians incur large switching costs, which are slightly reduced as learning occurs through additional prescribing of the drug. The fourth chapter uses the parameter estimates from the demand model to compare welfare under counterfactual simulations. The simulations show that policies that reduce physician switching costs, such as removing the

availability of brand-name drugs once the generic enters, can increase physician welfare and decrease average patient copays.

The fifth and final chapter concludes: summarizing the findings and laying out recommendations for future work.

CHAPTER 1

INTRODUCTION

1.1 Overview

Pharmaceutical spending in the United States is high—$333.4 billion in 2017—and accounts for ten percent of total national health spending. Brand-name drugs represent 15 percent of the share of total dispensed drugs but 87 percent of pharmaceutical spending (49). There is a vigorous policy debate on lowering prescription drug spending, where widespread use of generic drugs could play a large role in decreasing costs. In many cases, brand-name drugs continue to be prescribed and filled despite the availability of lower-cost generic drugs. Although there are many institutional features designed to encourage generic drugs as the default drug choice,[1] brand-name drugs maintain considerable market share even after generics become available.

In an ecosystem designed to promote generic use, the switch from brand-name to generic drugs is slow and costly to patients and insurers. Between 2000 and 2004, the delayed uptake of generic drugs cost Medicaid an estimated $1.5 billion (46). An $1,606 additional dollars are spent annually on atypical antipsychotics per patient due to the slowed transition to generics.[2]

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[1]State-level generic substitution laws urge or mandate pharmacists to make patients aware of generic drug availability and recommend patients switch to the lower-cost alternative. Health insurers typically assign higher copays to brand-name drugs when the generic equivalent becomes available to encourage generic utilization.

[2]Based on calculations from the data.

Patients, on average, spend 114 percent more on copays to stay on the brand-name version of an atypical antipsychotic. When generic Prozac, an antidepressant, became available, state Medicaid programs lost a total of $220 million between 2001 and 2005 due to slow generic uptake (44). As such, it is important to understand why certain classes of drugs have slow generic uptake in order to develop policies than can curb high pharmaceutical spending.

I estimate the effects of physician and patient familiarity with brand-name drugs on generic drug utilization. Using claims data on atypical antipsychotics from a large, national health insurer from 2012 to 2015, I document that physicians exhibit significant choice persistence for brand-name drugs when lower-cost generics are available. Choice persistence toward the brand-name drug is driven by physician preferences, not patients. I then address two possible factors of choice persistence in this paper: switching costs and learning. Switching costs may occur due to risk aversion and concerns about medication adherence—patients' current brand-name drugs may be working well and physicians may be hesitant to switch. Learning may occur in response to quality misconceptions about the generic drug. Physician concerns about quality and efficacy may be allayed through a Bayesian learning process in which physicians come to understand the quality of the generic drug over the set of a physician's patients. Many papers examine Bayesian learning in physician prescribing behavior for anti-ulcer medications (11; 12), antihistamines (51), and antidepressants (21). I build on this literature by allowing for within-molecule learning and switching costs following generic entry. The source of brand-name choice persistence has important welfare considerations. If physicians experience switching costs, investments in interventions to make physicians less inertial will be beneficial. Such interventions include

nudges in electronic health records at the hospital/health-system level, changes to state-level mandatory generic substitution laws, and increasing physician awareness on copay differentials and the side effects of the generic. However, if physicians' choice persistence is a function of the time it takes to learn, these investments may not be worthwhile if learning occurs quickly and physicians make the welfare-enhancing choice eventually.

This paper studies inertia in the context of atypical antipsychotics. Atypical antipsychotics, or "second-generation" antipsychotics, are used to treat schizophrenia, bipolar disorder, and major depression, among other mental health disorders. Mental health prescriptions represented 403 million prescriptions in 2017—nearly seven percent of all prescriptions filled—and per capita usage increased 28 percent since 2008 (42). I focus on this drug class for several reasons. Atypical antipsychotics treat chronic mental health conditions. Patients are not cured by taking these drugs, making it a salient drug class in which to study inertia and choice persistence. Additionally, atypical antipsychotics were often top selling drugs prior to their patent expiry. Otsuka Pharmaceuticals' Abilify was the best-selling drug in the United States in 2014. There may be large welfare effects from generic availability and switching patterns in this class of drugs. Finally, the market for atypical antipsychotics is characterized by idiosyncratic preferences and risk aversion, due to the severity of patient illnesses, which may result in inertial behavior.

A key empirical challenge in prescribing markets is separating physician from patient preferences. I do so by comparing the choices made by patients and physicians familiar with the drug class before generic entry using a quasi-experimental, reduced form approach. I define physicians and patients as familiar with the drug class if they prescribed or filled atypical an-

tipsychotics before generic entry. I show that patient familiarity plays a small role—patients who are familiar with the drug class are 1.3 percentage points less likely to fill a generic prescription than unfamiliar patients, representing a 6 percent increase in the probability of brand-name drug use. Conversely, physicians who prescribe an atypical antipsychotic before generic entry are 3.6 percentage points less likely to prescribe the generic drug once it has become available than physicians who do not prescribe until after generic entry. This represents a 16 percent increase in the probability that a brand-name drug is prescribed after the generic is available. These results build on a literature that finds patient preferences play a small role in practice style variation (2; 27; 17).

Having established that atypical antipsychotic drug choice is driven by physicians, I then provide evidence of Bayesian updating as physicians understand the quality and efficacy of the generic entrant. Physicians have prior beliefs about the efficacy of the generic, which may differ based on their previous experiences and patient severity. Using a reduced form, event study approach, I show that switching from the brand-name drug occurs relatively quickly following generic entry. Physicians familiar with the drug class prescribe the generic drug at a significantly lower rate than physicians unfamiliar with the class only in the first month. By two months after generic entry, class-familiar and class-unfamiliar physicians prescribe generic drugs at the same rate, increasing their prescribing of the generic drug, as they understand the efficacy of the generic entrant and how their patients may respond. This contributes to the literature on physician learning in prescription drug choice.(11; 12) explore physician learning under uncertainty in anti-ulcer medications, where physicians make Bayesian updates to

their beliefs about the efficacy of medications. Other studies focus on antihistamines (51) and antidepressants (21).

Physician prescribing behavior and patient drug preferences may also be influenced by a myriad of tools used by pharmaceutical firms and policy makers. I expand the analysis to understand how copay coupons, marketing payments to physicians from pharmaceutical firms, and generic substitution laws are associated with the likelihood of generic prescribing. I show that these possible confounders are not driving choice persistence toward brand-name atypical antipsychotics.

Based on the reduced-form evidence, I develop a structural model for physician demand for atypical antipsychotics that defines parameters for switching costs and learning. This model allows me to separate unobserved persistent preference heterogeneity for brand-name drugs from structural choice persistence through a random coefficients mixed logit model. Random coefficients mixed logit models are commonly used in the health industrial organization literature. (30) identifies inertia using new user choice in health insurance plan choice. This work has been followed by a literature on Medicare Part D plan choice, notably (55), (36), and (38). I separate channels of switching costs and learning via a structural demand model for atypical antipsychotics which builds on the model presented in (22). My findings show that physicians are price inelastic with respect to their patients' atypical antipsychotic drugs, exhibiting an average price elasticity of -0.0007. I find that switching costs are high, with physicians willing to pay $647 on average to keep the patient on the brand-name version of the drug. Learn-

ing, in the form of accumulating experience prescribing the drug, is small, as each additional prescription of the drug reduces choice persistence by $22.

The demand model allows me to quantify changes in physician welfare under counterfactual simulations.[1] For each counterfactual, I also evaluate changes to average patient copays. I first consider a counterfactual in which I shut down the inertia channel by removing switching costs within drug molecules. This counterfactual is intended to apply broadly to policies that could decrease physician inertia, such as the provision of information on generic drug quality and patient copay differentials. Average physician welfare increases by about $7 per prescription when there are no within-molecule switching costs. On average, generic drug utilization and patient copays do not change under this counterfactual.

Additional counterfactual simulations allow me to model the influence that insurer incentives can have on prescribing practices. Specifically, I consider an insurance policy in which brand-name drugs are removed from the formulary once the generic versions becomes available. This counterfactual may also inform the welfare effects of mandatory generic substitution laws, in which pharmacists are required to switch patients to generic versions of the drug. Holding the choice set constant to the five drugs providing the highest utility, physician welfare increases $31 per prescription. The average copay paid by patients falls by approximately $6. I also explore the change in welfare under an increase in the copay differential between brand and generic drugs. Since demand for atypical antipsychotics is relatively price inelastic, the salience

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[1] I assume that physicians are at least partially altruistic, and therefore consider patients' health and utility when making a drug choice.

of a larger copay differential may incentivize physicians to be swifter in switching their patients to generic drugs. I find that increasing the copay differential has no effect on welfare at the median and does not change the percent of prescriptions for generics.

1.2 Background

1.2.1 Generic Drugs

For Food and Drug Administration (FDA) approval, generic drug manufacturers must prove bioequivalence, which requires the same amount of active ingredients to reach the patient's blood stream in the same amount of time as the brand-name drug. The approval process for generic drugs is abbreviated through an aptly named Abbreviated New Drug Application (ANDA).[1] Applicants do not need to provide evidence of safety and effectiveness through clinical trials. Generic drugs' efficacy and safety are linked with those of their brand-name equivalents (45).

However, generic drugs may differ from brand-name drugs in their inactive ingredients, such as dyes, preservatives, coating, or flavoring. It is possible, though unusual, for patients to experience different side effects on a generic drug based on inactive ingredients.

As pharmaceutical drugs are an experience good, there are unobservable qualities to the drug that can only be known to physicians by prescribing it and their patients using it.[2] Physicians may be aware of the drug but may not know how their patients will respond to the drug (in terms of side effects or allergic reactions to fillers, etc.) until they try the drug.

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[1] See (10) for a more thorough description of the generic and brand-name drug approval process.

[2] (52) provides a theoretical discussion of how firm behavior can shape learning for experience goods through price and advertising efforts.

There may also be quality misconceptions and efficacy concerns related to a new, generic entrant. Despite being an identical molecule, physician perceptions of generic drugs are mixed. About 50 percent of physicians are concerned with the quality of generic drugs. A quarter of physicians believe generic drugs to be less effective than their brand equivalents. However, this belief varies across physicians, with younger physicians and physicians in larger practices less concerned about differences in quality and more likely to use generics themselves (63).

Additionally, in this setting, physicians may be more hesitant to switch their patients to the generic drug. Patients being treated for a psychotic disorder may be suspicious, paranoid, or hostile toward the generic drug (20; 57; 69). Fearing a decrease in medication adherence, physicians may be reluctant to switch patients with schizophrenia or other psychological disorders to generic drugs. Partial or non-adherence is associated with worsening psychotic symptoms, increased aggression toward self and others, and increased risk of hospitalization or schizophrenic relapse (4).

1.2.2 Atypical Antipsychotics

Atypical antipsychotics are used to treat schizophrenia, bipolar disorder, major depression, and anxiety. The first atypical or "second generation" antipsychotic, clozapine, was approved by the FDA in 1989. In the early 1990s, additional atypical antipsychotic molecules were introduced and approved for widespread use for major depression, in addition to schizophrenia and bipolar disorder (13). These antipsychotics have fewer side effects related to suicidality and motor function and are shown to be more effective than "typical" antipsychotics (50).

TABLE I

FOCAL DRUGS AND PATENT EXPIRY DATES

Brand name	Molecule name	Manufacturer	Patent expiry date
Geodon	ziprasidone	Pfizer Inc.	March 2012
Seroquel	quetiapine	AstraZeneca	March 2012
Symbyax	fluoxetine/olanzapine	Eli Lilly & Company	June 2012
Abilify	aripiprazole	Otsuka Pharmaceutical	April 2015
Invega	palperidone	Janssen Pharmaceutical	September 2015

I focus on five atypical antipsychotics that go off patent in the 2012 to 2015 period. These drugs are Geodon, Seroquel, Symbyax, Abilify, and Invega.[1] Table I describes the molecules, manufacturers, and dates of generic entry. The loss of patent exclusivity provides the opportunity to study generic entry, exogenously changing the choice set of drugs available for physicians to prescribe their patients.

Atypical antipsychotics are a salient drug class on which to study inertia. First, psychotic disorders are chronic illnesses and patients are not cured by taking atypical antipsychotics. Treatment continues indefinitely and so it is possible to track patients over time in claims data. Drugs within the class are considered substitutes, though they differ greatly in their side effect profiles.[2] These differences primarily relate to diabetes, weight gain, and sedation/sleep patterns, and provide distinctions within the drug class other than copayment amounts. In the

[1] AstraZeneca released Seroquel Extended Release (XR) in 2007. See Appendix B for more discussion.

[2] A more comprehensive discussion of the clinical literature on adverse side effects in atypical antipsychotics can be found in (23).

years leading up to patent expiry, these brand-name drugs were often among the top selling drugs in the United States. This means there may be large welfare effects from generic availability and switching patterns. Further, generic drugs, as discussed in Section 1.2.1, may differ from the brand-name drug in terms of side effect profiles based on differences in dyes, coatings, and preservatives. Finally, atypical antipsychotics represent a market in which consumers have idiosyncratic preferences and therefore may be averse to switch.

1.3 Setting and Data

The data come from a national health insurance company that provides health insurance coverage to employers in the small group market. The data include medical and pharmaceutical claims, as well as individual-level enrollment data for enrolled employees and their dependents. The data span the years 2012 through 2015 and cover ten states: Arkansas, Delaware, Illinois, Missouri, Oklahoma, Pennsylvania, Tennessee, Texas, Wisconsin, and Wyoming. Eight of the ten states have permissive and explicit generic substitution laws, meaning the pharmacist can switch patients to generic drugs but must first acquire explicit patient consent. Tennessee has a permissive and presumed generic substitution law, where pharmacists can assume patient consent in switching to the generic drug. Wyoming has mandatory and presumed substitution law, where the pharmacist is required to switch the patient to a generic and may assume patient consent. In all cases, the patient can override the substitution and mandatory substitution laws are shown to have little effect (65). Additionally, physicians can override substitutions for the generic drug when writing the prescription (37).

In my setting, all patients are covered by one insurer serviced by one pharmacy benefits manager (PBM), creating a single prescribing ecosystem. The prescription setting is a noteworthy feature of the data as all patients and their physicians face the same insurer influence. I am unable to explore any spillover effects of how physician prescribing behavior may change across their patients covered by different insurance incentives. I address cost sharing incentives in the counterfactual analysis, exploring the effect of removing the brand-name drug from the formulary once the generic becomes available and altering copay differentials between the brand and generic drugs. Pharmaceutical benefits vary across individuals only in the copayment regimes, which provide the copay amount patients face for different drugs. When employees select a health insurance plan from a firm's offerings, they are aware of the pharmaceutical copay regime. The formulary, or prescription drug list, sorts drugs into tiers, where drugs in higher tiers have more expensive copays. The formulary is consistent across plans.

At the firm level, plan offer data include the insurer's pharmaceutical plan codes. I infer the copay regime for each pharmaceutical plan based on all the pharmaceutical claims. Using the inferred copay regime, I sort brand-name drugs and their generic counterparts into tier classifications. I use an algorithm similar to (35) and (1). For each pharmaceutical plan code, I use all individuals and their pharmaceutical claims to infer the copay regime by finding the modal copay amounts. Based on the copay regime for each pharmaceutical plan code, an individual's pharmaceutical plan code, and copayment amount for an atypical antipsychotic, I then sort each atypical antipsychotic into a tier. In the choice model described in 3.1, I include

the copay amounts a patient would have faced under their pharmaceutical plan's copayment regime if their physicians had prescribed them an alternate drug.

1.3.1 Patient Data

Patient data are included in the pharmaceutical claims, medical claims, and enrollment data. I limit the data to individuals who fill a prescription for one of the five focal drugs or its generic over the 2012 to 2015 period. The pharmaceutical claims data provide prescription fill dates, National Drug Code (NDC), and copayment amounts. Using a unique enrollee identifier, I link the pharmaceutical claims to the medical claims and enrollment data. The medical claims contain dates of service, ICD-9 and ICD-10 diagnoses and procedure codes, and physicians' National Provider Identifier (NPI) records. Additionally, the enrollment data provide dates of health insurance plan enrollment, gender, and age of enrollees. From the medical claims, I identify patient diagnoses using ICD-9 and ICD-10 codes. The Agency for Healthcare Research and Quality's Clinical Classification Software (CCS) provides a diagnosis organization scheme that collapses diagnoses into a smaller number of clinically meaningful categories.[1]

Patient characteristics are summarized in Table II. I observe about seven prescription fills per patient. Patients receive prescriptions from nearly two physicians on average. 61 percent of the sample is female and the average patient is about 41 years old. 17 percent of patients have diabetes, 30 percent have hypertension, one percent have acute myocardial infarction (AMI), 11 percent have chronic obstructive pulmonary disease (COPD), and 13 percent have asthma.

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[1]For more information, see (25).

84 percent of the patients in my sample have a mood disorder (which includes bipolar disorder), 60 percent are diagnosed with an anxiety disorder, and 11 percent have schizophrenia.

My data require one member of a family to be employed by a firm, representative of half of the American public who receive insurance through their employer.[1]

1.3.2 Physician Data

The medical claims include NPI. I use Centers for Medicare and Medicaid (CMS) Physician Compare to gain information on physician characteristics, including year of graduation, practice size, and whether or not they use an electronic health record (EHR).

Table III summarizes physician characteristics. On average, physicians write five prescriptions for atypical antipsychotics for just over one patient. 31 percent of physicians are female. The average physician has been in practice for 23 years and has a practice size of roughly 200. 45 percent use an EHR. The most common specialties are family medicine, internal medicine, and psychiatry.

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[1]See https://www.kff.org/other/state-indicator/total-population/.

TABLE II

PATIENT CHARACTERISTICS BY FAMILIARITY STATUS

		Drug class		Molecule	
	All Mean/SD	Unfamiliar Mean/SD	Familiar Mean/SD	Unfamiliar Mean/SD	Familiar Mean/SD
Number of fills	6.95	6.16	8.46	6.39	8.29
	(8.75)	(7.86)	(10.05)	(8.30)	(9.78)
Number of physicians	1.89	1.81	2.12	1.85	2.08
	(1.46)	(1.36)	(1.65)	(1.43)	(1.60)
Age	40.85	39.96	41.25	39.92	41.31
	(15.67)	(15.42)	(15.95)	(15.45)	(15.93)
Female	0.61	0.59	0.63	0.59	0.63
	(0.49)	(0.49)	(0.48)	(0.49)	(0.48)
Chronic condition diagnoses					
Diabetes	0.17	0.16	0.17	0.16	0.17
	(0.37)	(0.37)	(0.38)	(0.37)	(0.38)
Hypertension	0.30	0.30	0.30	0.30	0.30
	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)
AMI	0.01	0.01	0.01	0.01	0.01
	(0.08)	(0.08)	(0.08)	(0.09)	(0.07)
COPD	0.11	0.11	0.11	0.11	0.11
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Asthma	0.13	0.14	0.13	0.14	0.13
	(0.34)	(0.35)	(0.34)	(0.35)	(0.34)
Mental health diagnoses					
Adjustment	0.13	0.14	0.13	0.14	0.13
	(0.34)	(0.34)	(0.34)	(0.34)	(0.34)
Anxiety	0.60	0.65	0.58	0.65	0.57
	(0.49)	(0.48)	(0.49)	(0.48)	(0.49)
Mood	0.84	0.83	0.87	0.83	0.87
	(0.37)	(0.38)	(0.34)	(0.37)	(0.34)
Personality	0.05	0.06	0.05	0.06	0.05
	(0.22)	(0.24)	(0.22)	(0.24)	(0.22)
Schizophrenia	0.11	0.13	0.11	0.13	0.11
	(0.31)	(0.34)	(0.31)	(0.34)	(0.31)
Observations	9064	4822	4894	4944	4772

Notes: Observations are at the patient level.

TABLE III

PHYSICIAN CHARACTERISTICS BY FAMILIARITY STATUS

		Drug class		Molecule	
	All Mean/SD	Unfamiliar Mean/SD	Familiar Mean/SD	Unfamiliar Mean/SD	Familiar Mean/SD
Number of prescriptions	4.96	4.64	6.97	5.31	6.34
	(7.91)	(6.69)	(11.51)	(9.00)	(9.90)
Number of patients	1.35	1.36	1.70	1.48	1.57
	(1.28)	(1.05)	(2.05)	(1.56)	(1.70)
Female	0.31	0.31	0.31	0.30	0.31
	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)
Years in practice	22.64	22.50	23.00	22.60	22.92
	(10.85)	(10.84)	(10.72)	(10.80)	(10.76)
Practice size	199.21	199.28	201.82	199.24	202.01
	(393.51)	(385.66)	(403.74)	(386.12)	(404.23)
Uses EHR	0.45	0.44	0.46	0.44	0.46
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Common Specialties					
Family medicine	0.24	0.23	0.25	0.24	0.25
	(0.43)	(0.42)	(0.43)	(0.42)	(0.43)
Psychiatry	0.10	0.11	0.12	0.12	0.11
	(0.30)	(0.31)	(0.33)	(0.32)	(0.32)
Internal medicine	0.15	0.15	0.16	0.15	0.15
	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)
Observations	12692	7286	6993	7659	6620

Notes: Observations are at the physician level.

CHAPTER 2

DO PATIENTS OR THEIR PHYSICIANS MAKE DECISIONS?: A QUASI-EXPERIMENTAL APPROACH

2.1 Conceptual Framework

The goal of this section is to document the existence of inertia in prescriptions for brand-name atypical antipsychotics. I explore physician and patient inertia separately and their interaction. I aim to understand whether physician or patient preferences are the main reason for why brand-name drugs continue to be filled despite the availability of cheaper generic alternatives. I then use an event study approach to highlight the Bayesian learning process for physicians.

Figure 1 shows the generic fill rate by the number of months following generic entry for each of the five focal drug molecules. For the majority of drugs, generics represent less than 20 percent of fills for the molecule in the first month. It takes between five and nine months for each generic drug to reach 80 percent of fills for the molecule. Full generic utilization can take several additional months to reach and few drugs ever do. Figure 2 plots the average monthly copay amount for each molecule's brand-name and generic versions. In each graph, the vertical line represents the month of generic entry. There is notable variation in the copay differences between the brand-name drug and generic drug across molecules. Copay amounts for the brand-name drug are about twice the generic copay amount. Brand-name drugs are

dominated in price and yet continue to be prescribed and filled. Higher copays for brand-name drugs and generic substitution laws make the slow uptake of generic drugs surprising and provide evidence for choice persistence.

The source of inertia is marked by the classical principal-agent problem found in medical decision-making. Patients may form their own drug preferences, influenced by word-of-mouth or direct-to-consumer advertising (DTCA). DTCA drives consumers into the market and benefits all products within a drug class (61; 64), producing spillovers to other brand-name drugs or generic versions. Copay coupons may also shape patient preferences by decreasing the out-of-pocket expense for brand-name drugs. Copay coupons decrease generic utilization (19), though are not often used (58).

Certain types of patients may also exhibit preferences for playing a larger role in the medical decision-making process. Younger adults and individuals with higher incomes and education levels express a greater desire for active participation in the decision-making process (9; 67). Highly-educated patients, particularly those with medical or pharmaceutical degrees, may be more likely to choose the generic drug (3; 43).

However, a large literature on physician practice style and variation has shown that patient preferences play a small role in practice variation (2; 27; 17). (17) find physician beliefs about treatment factor most strongly in practice variation. In 2017, generic drug use represented 84 percent of all prescriptions in the United States (60). Yet physicians' beliefs about generic drug quality and efficacy vary—a quarter of physicians believe generic drugs to be less effective than their brand-name equivalents and 50 percent of physicians express concern about the quality

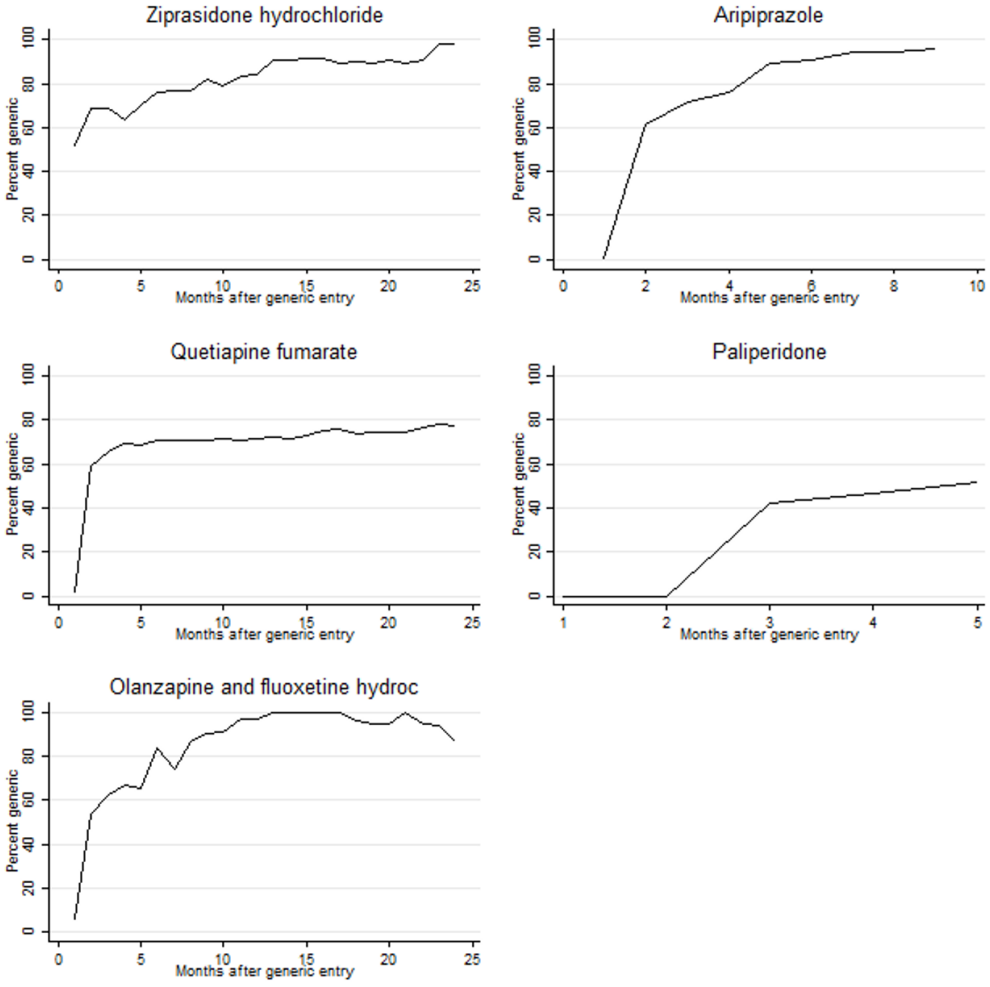

Figure 1. Average generic fill rate following generic entry

Notes: Figures show, for each drug molecule, the percentage of prescriptions filled as generic by the number of months following generic entry.

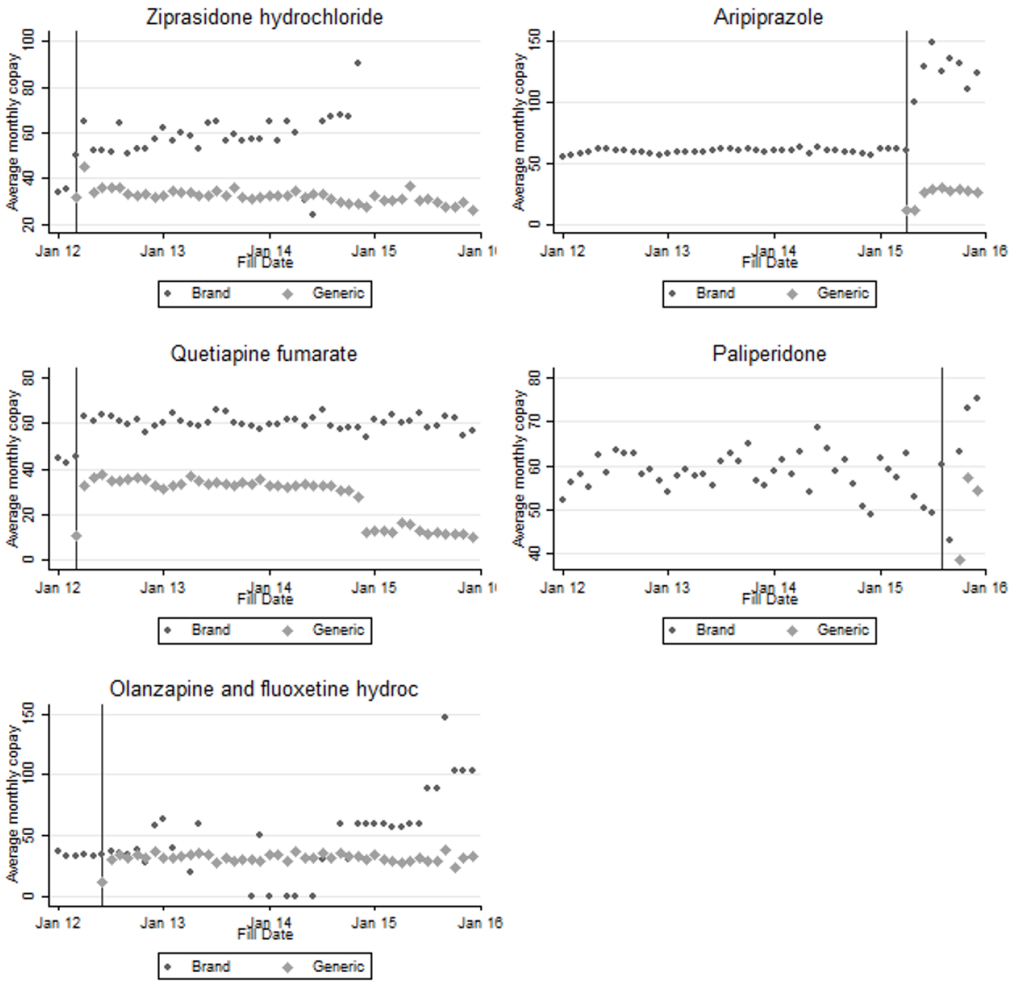

Figure 2. Patient spending (copays) for brand and generic drugs

Notes: Figures show, for each drug molecule, the average monthly copay amount by month. The vertical line marks the month of generic entry for each drug molecule. Copays are weighted to a 30-day amount for individuals prescribed in 60- or 90-day quantities. Small variations in mean copay amount from month to month arise from differences in individuals' copay regimes, frequent updates to the insurer's formulary, and an unbalanced panel. Brand copays are dark grey circles, generic copays are light grey diamonds.

of generic drugs. Younger physicians and those in larger practices are less concerned about quality and more likely to use generics themselves (63).

Physician expertise and diagnostic skill also play an important role in variation in physician behavior (16; 14; 15). (15) develop a model where physician diagnostic skill and taste for experimentation influence the antidepressant prescribed by a physician. (37) finds that physicians are an important agent in the brand-name versus generic decision.

Physicians may also consider how patients will respond to the switch to the generic drug and choose to keep their patients on the brand-name drug to promote medication adherence. In the case of atypical antipsychotics, patients may be skeptical about switching to the generic drug, becoming suspicious, paranoid, or hostile toward the generic drug (20; 57; 69). Physicians may paternalistically choose to have their patient remain on the brand-name drug so as not to experience decreased medication adherence, which is associated with worsening psychotic symptoms and increased risk of hospitalization (4).

In the remainder of this section, I use a quasi-experimental approach to determine if physician or patient preferences are the source of inertia toward brand-name atypical antipsychotics. I then use an event study to assess Bayesian learning for physicians about the quality and efficacy of new generic entrants.

2.2 Inertia in Drug Choice—Methods

To compare physician and patient preferences, I test for physician and patient inertia in the prescription drug choice. An ideal experiment would compare physicians and patients who first made a drug choice under the brand-only choice set to physicians and patients who do not make

a choice until after the generic drug is available. In this comparison, physicians and patients whose first choice is after generic availability are not subject to inertia. This comparison is in the spirit of (30), which studies the behavior of new employees' health insurance choice over time.

I use the following regression to find evidence of inertia:

$$Generic_{ikt} = \alpha + \beta Familiar_{ik} + \lambda X_i + \gamma Z_k + \delta_t + \xi_s + \eta_j + \varepsilon_{ikt}. \tag{2.1}$$

$Generic_{ikt}$ is a dummy variable equal to one if the drug is a generic. $Familiar_{ik}$ is a measure of physician or patient familiarity with the molecule or drug class, described in more detail below. X_i is a vector of physician characteristics, including gender, practice size, EHR use,[1] number of years since medical school graduation, and specialty fixed effects. Z_k is a vector of patient characteristics, including age, gender, and diagnoses. I also include indicators for the type of plan in which the patient is enrolled (e.g., health maintenance organization (HMO), preferred provider organization (PPO), etc.).[2] I also include month-since-generic-entry and month-year fixed effects (δ_t), state fixed effects (ξ_s), and drug molecule fixed effects (η_m). The reduced form analysis only includes prescriptions filled after generic availability.

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[1]The default drug in an EHR is a significant determinant of generic drug-use—for internal medicine physicians changing the default drug increased generic prescribing rates by 5.4 percentage points (53).

[2](59) finds that physicians in HMOs are sensitive to insurer drug procurement costs and are more likely to prescribe generic drugs.

2.3 Results

2.3.1 Patient Inertia

I compare patients who filled a prescription for an atypical antipsychotic before generic entry to those who did not begin using the drug until after generic entry. If patient preferences are driving drug choice, then we would expect a negative effect for patient familiarity. I define patient familiarity in two ways: patients who are familiar with the atypical antipsychotic drug class (observed filling any atypical antipsychotic) before generic entry and patients who are familiar with the drug molecule (observed filling the brand-name drug) before the generic equivalent enters.

I also define familiar patients as patients who are diagnosed with a mental health disorder before generic entry. This definition is aimed at capturing patients who may have irregularly filled their prescription or were less adherent to their drugs. The results for this measure are in Table XX, Appendix A and are similar to estimates presented in this section. Familiar patients are 2 percentage points less likely than unfamiliar patients to use the generic drug once it is available.

Summary statistics for the two measures of familiar patients are compared in Table II. Patients who are familiar with the drug class before generic entry are older and more likely to be female than class-unfamiliar patients. They are similar in levels of chronic condition diagnoses and mental health diagnoses. Table IV, Panel A, Column 1 presents the results for Equation 2.1 using patients with drug class familiarity as $Familiar_{ik}$. Drug-class familiar patients are 1.1 percentage points less likely to use the generic drug than class-unfamiliar

patients, significant at the five percent level. Given that generic drugs represent approximately 78 percent of prescriptions once they are available, this translates to a five percent increase in brand-name drug utilization.

I then define $Familiar_{ik}$ as a patient who filled the brand-name drug before its generic equivalent became available. Table II shows that patients who are familiar with the drug molecule are similar to patients familiar with the drug class. Results for this measure of $Familiar_{ik}$ from Equation 2.1 are in Table IV, Panel B, Column 1. Molecule-familiar patients are 1.7 percentage points less likely to use the generic once it is available, translating to an eight percent increase in brand-name drug utilization.

An unbiased estimate of the causal effect of patient familiarity requires the assumption that when patients begin taking an atypical antipsychotic is as good as random conditional on covariates. For this to be true, patients should not wait until the generic is available to start taking an atypical antipsychotic. With five focal drugs going off patent at different times over the period, this would require patients to know which drug is best suited for them and when this drug will be going off patent. While this information is publicly available, it is unlikely that patients are waiting to treat mental health conditions until a generic drug is available. Figure 9, Appendix A shows that there are no large jumps in the number of fills the month of or after generic entry, suggesting that patients are not waiting to fill their prescriptions until the generic version is available. Some drug fills (e.g., Olanzapine and fluoxetine, aripiprazole, and paliperidone) even decrease the first month the generic drug is available.

TABLE IV

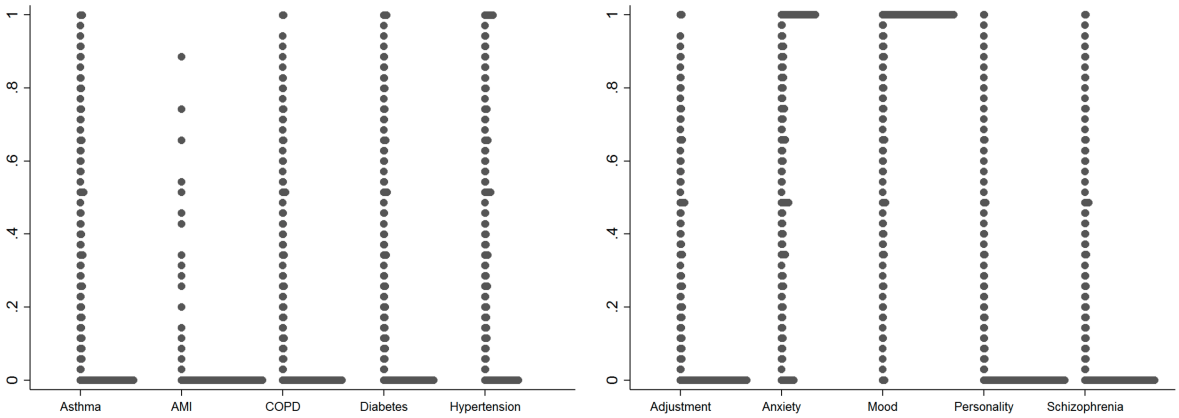
EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Panel A: Familiarity with drug class before generic entry				
Class-familiar patient	-0.0112*		0.0053	-0.0028
	(0.0055)		(0.0061)	(0.0075)
Class-familiar physician		-0.0364***	-0.0387***	-0.0494***
		(0.0057)	(0.0063)	(0.0085)
Class-familiar physician				0.0217
× Class-familiar patient				(0.0116)
Adjusted R^2	0.081	0.082	0.082	0.082
Observations	36769	36769	36769	36769
Panel B: Familiarity with drug molecule before generic entry				
Molecule-familiar patient	-0.0169**		-0.0008	-0.0102
	(0.0057)		(0.0066)	(0.0076)
Molecule-familiar physician		-0.0341***	-0.0337**	-0.0538**
		(0.0061)	(0.0070)	(0.0109)
Molecule-familiar physician				0.0331*
× Molecule-familiar patient				(0.0135)
Adjusted R^2	0.081	0.082	0.082	0.082
Observations	36769	36769	36769	36769

Notes: Table shows the results from Equation 2.1. Observations are at the prescription level. All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, plan type fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

2.3.2 Physician Inertia

Next, I turn to physician inertia. I first show that within-physician, there is substantial variation in patient characteristics. Figure 3 plots physician variation in the average characteristics of their patients. For both chronic conditions (left panel) and mental health conditions (right panel), it is clear that physicians treat a range of patients.



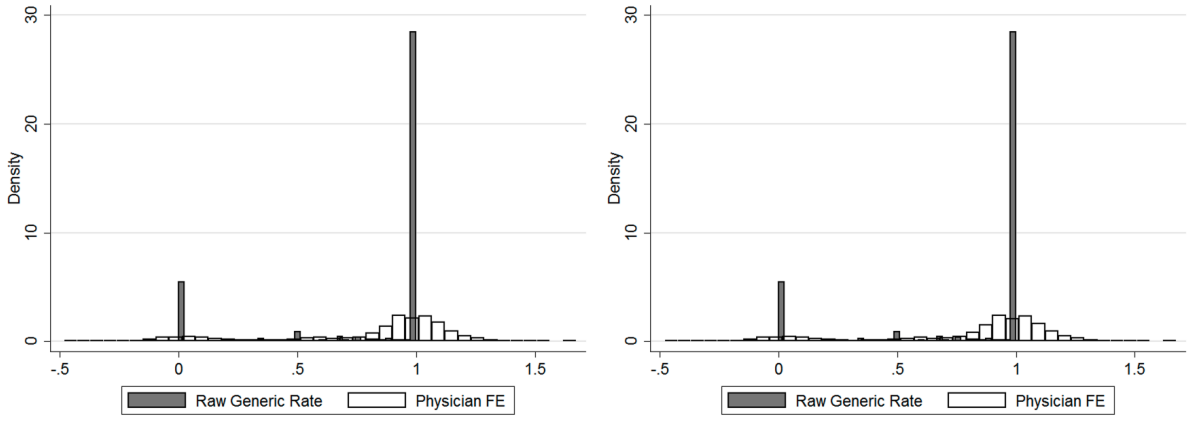
Chronic Condition Diagnoses | Mental Health Diagnoses

Figure 3. Variation in patient characteristics by physician

Notes: Figures are dot plots for physicians' average patient characteristics. The left panel shows physicians' average diagnoses of patients with chronic conditions. The right panel shows average diagnoses of patients with selected mental health diagnoses. The sample is limited to physicians with more than one patient on atypical antipsychotics.

I then expand Equation 2.1 to include a physician fixed effect. This model uses within-physician variation in patient familiarity and other patient characteristics. Variation comes from physicians who have multiple patients, some of whom are familiar with the drug class

or molecule and others who do not. The magnitude and significance of the patient familiarity effect, presented in Panel A of Table V, is similar to that found in Table IV. This model also shows substantial physician variation in generic prescribing rates net of patient characteristics. Figure 4 plots the physician fixed effects overlaid with the raw generic prescribing rates observed in the data. Controlling for patient characteristics, including patient familiarity with the drug class or molecule, physicians still have significant variation in their generic prescribing rates.



Patient familiarity with drug class Patient familiarity with molecule

Figure 4. Physician variation in generic prescribing

Notes: Figures plot the distribution of generic prescribing rates after generic entry for physicians against the distribution of physician fixed effects from an adapted version of Equation 2.1.

There is large within-physician variation in patient characteristics and net of these characteristics, physicians still have significant variation in their generic prescribing rates. I compare physicians who prescribed atypical antipsychotics before generic entry to those who did

not prescribe until after generic entry. I consider two measures of physician familiarity. The first measure considers physicians who prescribed any atypical antipsychotic (inclusive of other generics) before generic entry and are familiar with the drug class. The second measure considers physicians who prescribed the brand equivalent before generic entry and are familiar with the molecule.

I also consider a third familiarity measure for physicians who were in practice before generic entry. I determine the year a physician started practicing from the year they graduated medical school according to the Physician Compare database. While intuitively appealing, this measure is logistically difficult to implement. Only 80 out of 12,692 physicians in my sample begin practicing after generic entry, so there is little variation in drug familiarity. Additionally, rather than capturing the effect of familiarity with the drug class or molecule, this variable may capture the effect of having been in practice longer. Results using physicians practicing before generic entry as the physician familiarity measure are included in Table XX, Appendix A. Physicians practicing before generic entry are not statistically different in the likelihood of prescribing a generic drug than physicians who do not begin practicing until after generic availability.

I first define the familiarity measure on the basis of drug class familiarity. Table III shows summary statistics for physicians by familiarity type. Drug class-familiar physicians are very similar to class-unfamiliar physicians who do not begin prescribing until after the generic is available. Class-familiar physicians are two percentage points more likely to use an electronic health record and more likely to be among the top three specialties of family medicine, psychi-

atry, and internal medicine. Table IV, Panel A, Column 2 reports results for physician inertia using this measure of $Familiar_{ik}$. Physicians familiar with the drug class prior to generic entry are 3.6 percentage points less likely to prescribe the generic once it is available. This translates to a 16 percent increase in brand-name drug utilization. Table XXI, Appendix A allows the drug-class familiarity effect to vary by the number of distinct molecules the physician has prescribed before generic entry. Physicians prescribing just one molecule before generic entry exhibit the largest inertial behavior, though physicians with experience with two molecules or three or more molecules are also significantly less likely to prescribe the generic drug than drug-class unfamiliar physicians.

I then define $Familiar_{ik}$ as physicians who prescribed the brand equivalent before generic entry, capturing familiarity with the drug molecule. The final two columns of Table III compare the characteristics of molecule-familiar physicians to molecule-unfamiliar physicians who did not begin prescribing the molecule until after generic entry. Physician characteristics vary similarly across the familiar and unfamiliar groups as they did for physicians prescribing any atypical antipsychotic before generic entry. Table IV, Panel B, Column 2 shows the familiarity effect for physicians prescribing the brand equivalent before generic entry. Molecule-familiar physicians are 3.4 percentage points less likely to prescribe the generic once it is available than molecule-unfamiliar physicians, equivalent to a 15 percent increase in brand-name drug prescribing.

The results largely confirm the literature on physician practice style and variation. Physicians familiar with the drug class or molecule are driving the treatment choice to remain on the

brand-name drug, as they may be more knowledgeable about risks of non-adherence associated with switching drug treatments.

TABLE V

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—ROBUSTNESS CHECKS

	Familiarity with drug class	Familiarity with molecule
	(1)	(2)
	Generic	Generic
Panel A: Patient inertia with physician fixed effects		
Familiar patient	-0.0099	-0.0235
	(0.0130)	(0.0130)
Adjusted R^2	0.659	0.659
Observations	36769	36769
Panel B: Physician inertia—Observed first fills only		
Familiar physician	-0.0536**	-0.0288
	(0.0207)	(0.0251)
Adjusted R^2	0.081	0.079
Observations	2872	2872

Notes: Table shows the results from Equation 2.1. Observations are at the prescription level. Panel A includes a vector of patient characteristics X_k, and month-since-generic-entry, month-year, state, drug molecule, and physician fixed effects. Panel B includes a vector of physician characteristics X_i, patient characteristics Z_k, and month-since-generic-entry, month-year, state, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

2.3.3 Interaction of Physician and Patient Inertia

I augment the basic model to include both physician and patient familiarity variables and their interaction. With this specification, I can directly compare the magnitude of coefficients for familiar physicians and familiar patients from the same specification.

Columns 3 and 4 of Table IV reports the results. In Column 3, I include measures of both patient and physician familiarity. For both class- and molecule-familiar patients, the familiarity effect is small and insignificant. Physicians familiar with the drug class before generic entry are 3.9 percentage points less likely to prescribe the generic, while physicians familiar with the brand equivalent are 3.4 percentage points less likely. Controlling for patient familiarity, physicians familiar with the class and molecule are more likely to prescribe the brand-name drug.

Column 4 introduces the interaction of physician and patient familiarity. Across both measures of familiarity, the interaction between familiar physician and familiar patient is positive and insignificant. Familiar patients have a small, negative effect, and when taking into account the interaction, do not differ from unfamiliar patients in the probability of filling a generic drug. Familiar physicians, on the other hand, have a large, significant, negative effect. Drug-class familiar physicians with unfamiliar patients are 4.9 percentage points less likely to prescribe a generic drug. Physicians familiar with the drug class exhibit inertia across their patients who are both familiar and unfamiliar with the drug class, as they are no less likely to prescribe the generic to familiar patients as they are to unfamiliar patients. Molecule-familiar physicians are 5.4 percentage points less likely to prescribe a generic. Taking into account the interaction

term, familiar physicians are between 2.1 and 2.8 percentage points less likely to prescribe the generic than unfamiliar physicians once the generic has become available.

This analysis provides evidence that physicians drive inertia toward the brand-name atypical antipsychotic. Physicians exhibit choice persistence and continue to prescribe brand-name drugs despite generic availability. To test this further, I restrict the data to use only observations from the first time I observe a patient. While not a perfect measure since I do not have a complete prescription history, this is intended to proxy for patients who are filling an atypical antipsychotic for the first time. These patients are presumably unfamiliar with the choice set (e.g., they have not previously had a positive or negative experience with an atypical antipsychotic). Results are reported in Table V, Panel B. Physicians with drug class familiarity before generic entry are 5.4 percentage points less likely to prescribe the generic once it becomes available. The molecule-familiar physician effect suggest inertia exists, though is not statistically significant.[1]

2.4 Learning in Drug Choice—Methods and Results

Having established that inertia in atypical antipsychotic drug choice after generic entry is driven by physician preferences, I provide reduced form evidence that physician inertia may be due to the time it takes to learn. Specifically, I explore whether learning about the quality and efficacy of the new, generic drug follows a Bayesian process. Atypical antipsychotics are

[1]Table XXII, Appendix A excludes refills from the sample. Results are similar in magnitude; however, in Column 4, the interaction term shows that molecule- and drug-familiar physicians are significantly more likely to prescribe the generic version for their familiar patients than for non-familiar patients.

an experience good and therefore individuals may not know the utility they derive from a new drug until they try it for themselves. After the generic drug becomes available, physicians may be risk-averse in prescribing because of unknown side-effect differences from the brand-name drug or other reasons related to drug quality. Additionally, physicians may have further concerns about patient medication non-adherence if they switch the drug the patient is taking. Physicians have prior beliefs about the efficacy of the generic entrant that may differ based on previous experiences prescribing generic drugs and patient severity.

To formally test for learning following generic availability, I adapt Equation 2.1 to include an interaction term with a dummy variable for each of the months following generic entry, as shown by the following equation:

$$Generic_{ikt} = \alpha + \sum_{t=1}^{12} \beta_t (Familiar_i \cdot Months_t) + \lambda X_i + \gamma Z_k + \delta_t + \xi_s + \eta_d + \varepsilon_{ikt}. \quad (2.2)$$

This equation allows for the experience effect to vary each month after generic entry.[1] The omitted reference period is time after twelve months of generic entry.

Figure 5 plots the marginal effects for familiar and unfamiliar physicians. The left panel of Figure 5 shows the results when $Familiar_i$ reflects drug class familiarity before generic entry, whereas the right panel shows the results for molecule-specific familiarity. For both measures, learning occurs quickly following generic entry. In the first month after the generic is available,

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[1] δ_t only includes month-since-generic-entry fixed effects. Month-year fixed effects are excluded from this model.

familiar physicians prescribe the brand-name drug at a significantly higher rate than unfamiliar physicians. In the second month after generic entry, generic prescribing rates are significantly higher for unfamiliar physicians, though the gap in generic prescribing rates for familiar and unfamiliar physicians has narrowed.

By three months after generic entry, familiar physicians prescribe the generic drug at a similar rate as unfamiliar physicians. However, only about 65 percent of prescriptions are for generic drugs. By six months following generic entry, the generic prescribing rate is about 80 percent for both familiar and unfamiliar physicians, where it remains for the next several months. Indeed, referring back to the raw generic prescribing rates in Figure 1, the generic rate for both Geodon (ziprasidone hydrochloride) and Symbyax (olanzapine and fluoxetine hydrochlorice) does not exceed 90 percent until nearly two years following generic entry.[1]

Both drug class- and molecule-familiar physicians have slightly lower generic prescribing rates than unfamiliar physicians in the months after generic entry, though these differences are insignificant in all but the first two months. This suggests that the learning process does not differ by familiarity with the drug class or molecule, but that all physicians are learning about qualities of the generic drug in the months following its availability.

2.5 Empirical Challenges and Confounders

There are two primary empirical challenges in this estimation strategy. First, there are threats to identification related to the conditional independence assumption. Second, due to

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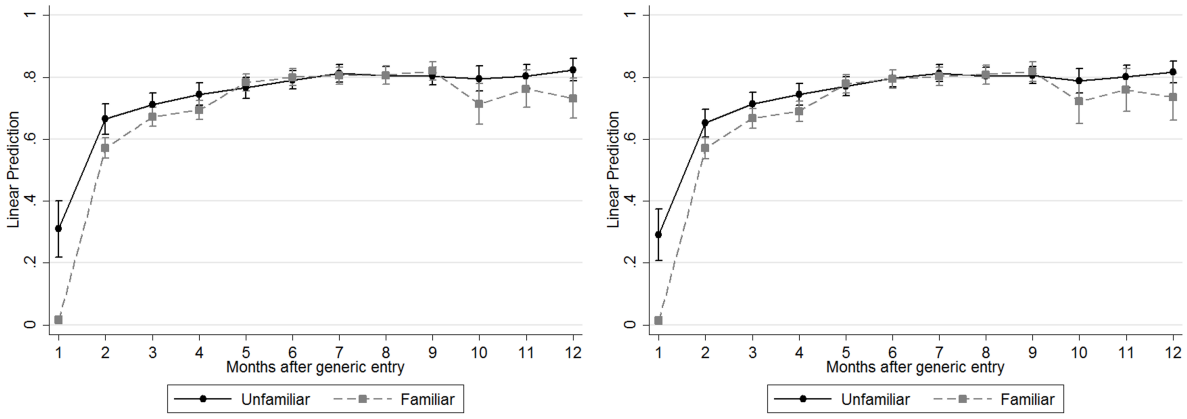
[1]Figure 11, Appendix A shows the results excluding refills. Results are similar.



Drug Class Familiarity Molecule Familiarity

Figure 5. Physician learning

Notes: Figures show the marginal effects and 95% confidence intervals for familiar and unfamiliar physicians from Equation 2.2. The left panel measures drug class familiarity. The right panel uses molecule familiarity.

data constraints, it is difficult to define familiarity. After addressing the empirical challenges, I then turn to a discussion of tools which may plausibly influence patient and physician inertia, in addition to learning. I consider confounders to inertia of manufacturer copay coupons, payments from pharmaceutical firms to physicians, and generic substitution laws. Such tools are used by pharmaceutical firms and policy-makers to either slow or encourage, respectively, the switch to generic drugs.

2.5.1 The conditional independence assumption and patient selection on severity

An unbiased estimate of the causal effect of physician familiarity requires the assumption that when physicians start prescribing atypical antipsychotics to their patients is as good as

random conditional on covariates. Variation in familiarity comes from the timing of when a physician treats patients requiring an atypical antipsychotic.

For unbiased estimates of physician familiarity in this setting, variation in patient characteristics should not be changing around the timing of generic entry. To test the conditional independence assumption, I regress patient characteristics on month-year fixed effects interacted with the drug-class familiar physician indicator, physician characteristics, remaining patient characteristics, month-since-generic-entry fixed effects, state fixed effects, and drug molecule fixed effects. Figure 6 plots the coefficients on the interaction of month-year fixed effects and the drug-class familiar physician measure. The left panel of Figure 6 shows the month-year-familiarity association with patient gender. In all months, the average patient gender for drug class-familiar and unfamiliar physicians does not statistically differ. The right panel of Figure 6 plots the analogous coefficients for a regression of patient schizophrenia diagnosis. Rates of schizophrenia diagnoses are not statistically different across familiarity levels.[1] These figures show that patient variation is not changing around the timing of generic entry and is not changing differentially for the class-familiar physician group or the class-unfamiliar physician group.

Specialists (i.e., psychiatrists) are more likely to see more severely ill patients and there is likely selection on severity. Psychiatrists are slightly more likely to be familiar with both the drug class and molecule. To address selection on severity and differences across specialists, I

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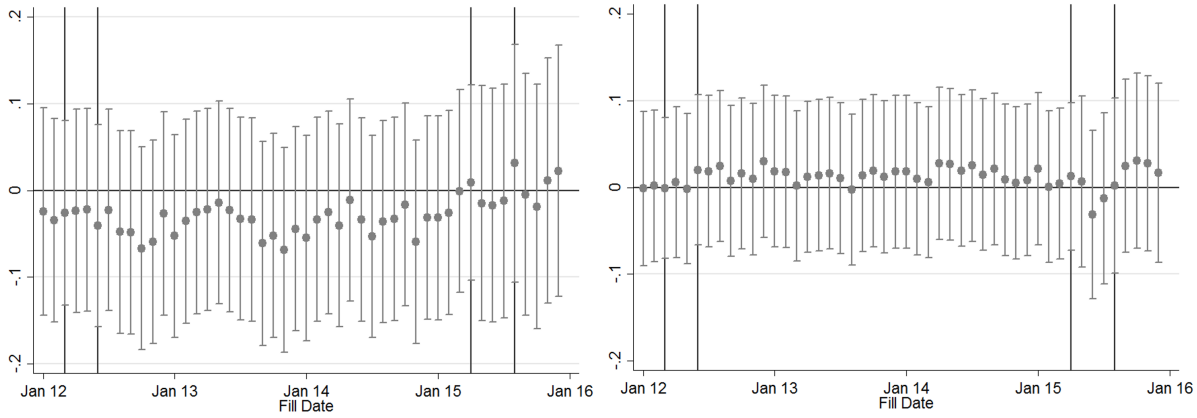
[1]Results for other patient characteristics are included in Figure 10, Appendix A.



Female Schizophrenia Diagnoses

Figure 6. Patient characteristics by physician drug class familiarity over time

Notes: Figures plot the coefficients on the interaction of month-year fixed effects and the drug-class familiar physician indicator from a regression of patient characteristics on month-year fixed effects interacted with the drug-class familiar physician indicator, physician characteristics, remaining patient characteristics, and month-since-generic-entry, state, plan type, and drug molecule fixed effects. The left panel uses patient gender as the outcome. The right panel uses schizophrenia.

stratify the sample to compare psychiatry to all other specialties. Since atypical antipsychotics are used to treat mental health disorders, we expect psychiatrists to be better identified as familiar physicians. Psychiatrists may also be more aware of both the choice set and generic availability. Table VI shows the results, where Column 1 shows results for all specialties other than psychiatry and Column 2 shows the results for psychiatry. Psychiatrists with familiarity are about 5.7 percentage points less likely to prescribe the generic, whereas other familiar physicians are between 1.5 and 2.2 percentage points less likely to prescribe the generic once it is available. Psychiatrists have larger familiarity effects and thus exhibit more inertia. This may be in part due to better identification of familiar psychiatrists, reflecting attenuation bias

for other specialties and the average results reported in Table IV. Psychiatrists may also be differentially concerned with issues of non-adherence, as they likely treat more severely ill patients.

TABLE VI

PHYSICIAN INERTIA BY SPECIALTY

	Other Specialties	Psychiatry
	(1)	(2)
	Generic indicator	Generic indicator
Panel A: Familiarity with drug class before generic entry		
Class-familiar physician	-0.0223***	-0.0563***
	(0.0066)	(0.0114)
Adjusted R^2	0.083	0.119
Observations	29798	6971
Panel B: Familiarity with molecule before generic entry		
Molecule-familiar physician	-0.0153*	-0.0568***
	(0.0070)	(0.0126)
Adjusted R^2	0.083	0.119
Observations	29798	6971

Notes: Table shows the results from Equation 2.1. Observations are at the prescription level. The sample is stratified by specialty, with results for psychiatry in Column (2) and all other specialists in Column (1). All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, plan type fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

2.5.2 Defining familiarity

The second empirical challenge is defining the familiar and unfamiliar groups. Ideally, I would compare physicians who first make a drug choice when only brand-name drugs are available to physicians who begin prescribing after generic entry. Physicians who begin prescribing once the generic is available are not subject to inertia. However, I face data limitations that do not allow me to identify treatment and control groups as cleanly as I would like. I only have data from one insurer and am unable to observe a physician's entire prescribing history across insurers. Additionally, for molecules that go off-patent in 2012, I have a limited pre-period in which to define familiarity.

2.5.2.1 Data from one insurer

I test how problematic it is that I only have data for one insurer by comparing states where the insurer has high market share to states where the insurer has low market share. From 2012 to 2015 for the ten states in my sample, the variation in the insurer's market share ranges from one percent to 58 percent. I compare the effect of physician familiarity in high market share states to low market share states, splitting the sample at the median market share in each year.[1] I interact high and low market share indicators with the familiarity indicators.

Table VII, Panel A reports the results of regressions with different effects for familiar physicians in high- and low-market share states. Physicians in high market share states exhibit more

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[1]Table XXIII, Appendix A summarizes the median market share and states that fall into the high and low market share categories in each year. Market shares are from the Kaiser Family Foundation: https://www.kff.org/other/state-indicator/market-share-and-enrollment-of-largest-three-insurers-small-group-market.

inertia—across both measures of familiarity, physicians prescribing before generic entry in high market share states are between 3.7 to 3.9 percentage points less likely to prescribe the generic once it is available than unfamiliar physicians. Drug class- and molecule-familiar physicians prescribing before generic entry in low market share states are between 3.1 and 3.3 percentage points less likely to prescribe the generic than unfamiliar physicians. The difference in familiarity effects between high and low market share states is not statistically significant. The pattern of magnitudes in the point estimates follows a trend we would expect due to measurement error in the classification of familiar physicians, with familiar physicians in lower market share states having an effect closer to zero.

2.5.2.2 Limited pre period

Defining treatment and control groups is also limited by when my data begin. My data begin in 2012, when the first group of atypical antipsychotics in my sample go off patent. For some drugs, I only have a few months during which to identify physicians with drug class- and molecule-familiarity. With an incomplete prescribing history, I may be misclassifying physicians who are actually familiar with the class or molecule in the control group. This would bias my results toward zero. To address the challenge in identifying physicians with familiarity, I compare the effect of physicians who are familiar with drugs that go off patent in 2012 to physicians who are familiar with drugs that go off patent in 2015. To do so, I interact indicators for the year in which the drug went off patent with the familiarity indicator. Table VII, Panel B reports results of regressions with different familiarity effects for 2012 and 2015 drugs. For these models, I limit the sample to only include prescriptions from within four months after

TABLE VII

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—ROBUSTNESS CHECKS FOR INCOMPLETE PHYSICIAN PRESCRIBING HISTORY

	Familiarity with drug class	Familiarity with molecule
	(1)	(2)
	Generic	Generic
Panel A: Physician inertia by market share		
Familiar physician × High market share	-0.0391***	-0.0369***
	(0.0068)	(0.0073)
Familiar physician × Low market share	-0.0333***	-0.0308***
	(0.0081)	(0.0088)
p-value for test of difference between treatment effects	0.542	0.564
Adjusted R^2	0.087	0.087
Observations	36769	36769
Panel B: Physician inertia by year of generic entry		
Familiar physician × 2012 drug	-0.0109	-0.0105
	(0.0211)	(0.0212)
Familiar physician × 2015 drug	-0.0406	-0.0435*
	(0.0227)	(0.0216)
p-value for test of difference between treatment effects	0.329	0.264
Adjusted R^2	0.14	0.14
Observations	4280	4280

Notes: Table shows the results from Equation 2.1. Observations are at the prescription level. Panels A and B include a vector of physician characteristics X_i, patient characteristics Z_k,and month-since-generic-entry, month-year, state, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

generic entry. This allows me to have the same amount of data after generic entry for each drug. Familiar physicians prescribing drugs that go off patent in 2015 are about four percentage points less likely to prescribe the generic. Familiar physicians prescribing 2012 off-patent drugs are just over one percentage point less likely to prescribe the generic. However, the difference in familiarity effects is not statistically significant at the five percent level. Again, the pattern of magnitudes in the point estimates suggests that my results are biased toward zero due to potential misclassification of familiar physicians as members of the unfamiliar, control group.

There are several factors that may alter inertia in drug choice that I address empirically. Such potential confounders include copay coupons provided to patients to cover some or all of their out-of-pocket costs for prescriptions drugs and marketing payments made from pharmaceutical firms to physicians. Additionally, variation in state generic substitution laws may also influence patient and physician inertia.

2.5.3 Copay coupons

Patient preferences for the brand-name drug may be influenced by the existence of copay coupons. Insurers attempt to steer patients toward lower cost drugs by sorting drugs into tiers, where more expensive, brand-name drugs have higher copays. These efforts may be thwarted by copay coupons from drug manufacturers, which offer to pay some or all of a patient's copay for the brand-name drug. (19) find that copay coupons decrease generic utilization by 3.4 percentage points. However, copay coupons were only used on between 5 and 11 percent of brand-name prescriptions dispensed in the United States in 2010 and 2011. In 2013, only 8.3 percent of available coupons were for a brand-name drug with an FDA-approved generic

equivalent (58). Copay coupons are available for three of the drugs in my sample: Abilify, Geodon, and Seroquel and reduce copays to about $5 for a monthly supply, about an eighth of what patients would pay for the brand-name drug without a coupon.

The existence of copay coupons may also introduce bias. Copay coupons are distributed to physicians' offices by pharmaceutical sales representatives. If pharmaceutical companies are more likely to provide coupons to physicians familiar with the drug class or molecule, due to industry relations, this may in part explain my main results. Similarly, my main results may be explained by copay coupons if patients with drug class- or molecule-familiarity know to seek out copay coupons from their physician or pharmacist. However, coupons are also distributed through pharmacies, in which case, the bias introduced by copay coupons would be limited to not being able to control for patients who use such coupons.

Table VIII, Columns 1 and 3 shows results for the effect of patient familiarity on the likelihood of filling a generic drug, stratified by whether or not the drug molecule has copay coupons available. Column (1) presents results for the two drugs without copay coupons and Column (3) shows results for the three drugs with copay coupons. Patients familiar with the drugs are about 7 percentage points less likely to fill a generic prescription for drugs without copay coupons, though this effect is insignificant (due to a lack of power). For drugs with copay coupons, familiar patients are between 1.1 and 1.7 percentage points less likely to fill a generic prescription.

While the results for the sample without copay coupons are insignificant, the larger point estimates suggest that copay coupons do not have a large additional impact on a familiar

TABLE VIII

PATIENT AND PHYSICIAN INERTIA BY DRUGS WITH COPAY COUPONS

	No Copay Coupon		Copay Coupons	
	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Panel A: Familiarity with drug class before generic entry				
Class-familiar patient	-0.0675		-0.0113*	
	(0.0532)		(0.0056)	
Class-familiar physician		0.0443		-0.0383***
		(0.0376)		(0.0058)
Adjusted R^2	0.480	0.479	0.076	0.077
Observations	766	766	36003	36003
Panel B: Familiarity with molecule before generic entry				
Molecule-familiar patient	-0.0703		-0.0171**	
	(0.0460)		(0.0058)	
Molecule-familiar physician		0.0099		-0.0358***
		(0.0352)		(0.0062)
Adjusted R^2	0.481	0.0478	0.076	0.077
Observations	766	766	36003	36003

Notes: Table shows the results from Equation 2.1. Observations are at the prescription level. The sample is stratified by whether the drug has a copay coupon available, with results for drugs with copay coupons (Abilify, Geodon, and Seroquel) in Column (2) and other drugs (Invega, Symbyax) in Column (1). All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, plan type fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

patient's choice to stay on the brand-name version of the drug. Biases for types of patients who seek out copay coupons may still be present, though the increased brand-name drug utilization

for familiar patients filling drugs without copay coupons suggests the bias may not be that large.

The effect of physician familiarity on the likelihood of filling a generic drug is in Table VIII, Column 2 for drugs without copay coupons and Column 4 for those drugs with copay coupons. The familiarity effect is driven by physician prescribing for drugs with copay coupons—familiar physicians are between 3.6 and 3.8 percentage points less likely to prescribe the brand-name drug when prescribing a brand-name drug with copay coupons. This provides suggestive evidence that physicians are responding to their patients' cost incentives.

2.5.4 Payments to physicians

Financial relationships between the pharmaceutical industry and physicians are common. In 2017, 628,000 physicians received a total of over $8.4 billion in payments from a pharmaceutical firm (6). The payments include consulting and speaking fees, research, meals, and travel reimbursement. The value of payments and the marketing they are associated with is potentially ambiguous. This form of advertising, or physician detailing, can be used to provide physicians with information such as a drug's existence or qualities (66). On the other hand, interactions with pharmaceutical firms and payments may be persuasive, making physicians feel beholden to a firm (56).

Payments are made by brand-name drug manufacturers to physicians, typically before the generic drug is available.[1] In this section I control for physician interactions with the pharma-

[1](48) show that over 99 percent of prescriptions for detailed drugs were for brand-name drugs with no generic equivalent.

ceutical industry since physicians who prescribed a drug prior to generic entry are more likely to have received payments from the pharmaceutical firm. Without controlling for these payments, if they are persuasive, my results for physician inertia would be downward biased away from zero. If pharmaceutical firms are more likely to provide payments to physicians familiar with the class or molecule, and these payments induce inertia toward the brand name drug, then physician-industry relationships may be driving the familiarity effect.

To shed light on physician relationships with pharmaceutical companies, I use the Open Payments data from the CMS. These data catalogue information about payments made by drug and medical device companies to physicians for travel, research, consulting, speaking fees, and meals. The data also include ownership interests that physicians or their families may have in these life sciences companies. Payment reporting is required under Section 6002 of the Affordable Care Act (ACA), also known as the Physician Payments Sunshine Act.[1] The reports are intended to increase transparency around the financial relationships between drug manufacturers and physicians. The Open Payments data became available starting August 1, 2013. Other research related to physician interaction with industry, notably (5) and (29), make use of data preceding the availability of Open Payments. (5) use the Pro Publica Dollars for Docs database from 2009-2013, which consists of once-publicly available data from lawsuit settlements. (29) use data from Kyruus, Inc. from this same time period collected in the same

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[1]Prior to the Sunshine Act, six states had mandatory reporting laws or bans on payments from pharmaceutical firms: Maine, Massachusetts, Minnesota, Vermont, West Virginia, and the District of Columbia. These states are not included in my sample.

fashion. These disclosures are ad hoc, though analysis by (29) show there is little evidence that the pre-Open Payments data is biased. Their analysis then also suggests that the passing of the Physician Payments Sunshine Act and the wide-spread disclosure and transparency it requires did not alter the nature of industry-physician interactions.

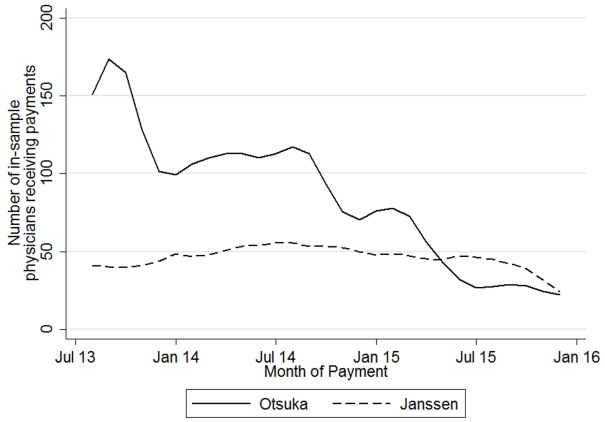
While the claims data begin in 2012, the payments data does not begin until August 2013. Some drugs (i.e., Geodon, Seroquel, Symbyax) are already off patent by the time the Open Payments begins. I create two variables that indicates payment receipt from the drug's manufacturing firm—the first variable considers payments only in promotion for one of the five atypical antipsychotics, while the second variable considers all payments from the focal pharmaceutical firm. These variables are both time-invariant for physicians. I also limit the data to prescriptions filled after August 1, 2013 and use time varying indicators for payment receipt in the same year and payment receipt in the same month. For payments in promotion of a focal drug, receiving a payment in the same month or year insignificantly reduces the probability of generic utilization by about 2.5 percentage points. Any payment from a pharmaceutical firm in the same month or year reduces generic utilization by roughly 5 percentage points, consistent with the time-invariant measure. Consistent with other findings, payment amounts matter less than does the entirety of the physician-industry relationship (5; 29).[1] For example, if a physician receives a payment from AstraZeneca in 2014, the payment receipt indicator when prescribing

[1]Regression results using time-variant payment receipt indicators and the actual payment amount received within a year are available upon request.

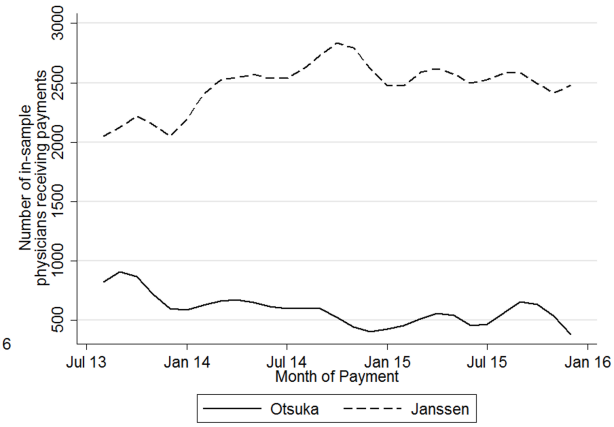
Seroquel is equal to one in 2012 as well. This construction may cause some measurement error in payment receipt and does not capture the dynamics of interactions with industry.

Defining payments as only those in promotion of a focal atypical antipsychotic may result in an underreporting of physicians who receive payments. Drug firms decrease promotional materials and marketing efforts for drugs with generic competition (40; 48). For the drugs that are already off-patent, marketing is likely reduced by the time the Open Payments data becomes available. The left panel of Figure 7 shows the decrease in payments as patent expiry approaches. Otsuka, the manufacturer of Abilify, decreases the number of payments it provides to physicians in my sample in the year before Abilify goes off patent in April 2015. Invega has fewer promotional payments made by Janssen right after the patent expires.

Using any payment from the firm as a proxy introduces additional noise, both in the firms that are promoting drugs to physicians and in the physicians' likelihood to receive payment. First, smaller pharmaceutical firms, such as Otsuka, have fewer drugs to promote. At this time, Pfizer is actively promoting Viagra and other top-selling drugs. Eli Lilly and AstraZeneca both are promoting various insulin products. This increases payment receipt from specific, large manufacturers. Second, general physicians (e.g., family medicine and internal medicine specialists) are more likely to receive payments as they are the target for additional drugs. The right panel of Figure 7 highlights the measurement error in defining payments as any payment made by the pharmaceutical firm. The total number of payments made by Otsuka is declining, while Janssen increases the number of physicians they pay as they market other drugs in their portfolio still on patent, such as the blood thinner Xarelto.



Payments in Promotion of Focal Atypical Antipsychotic Drugs



Payments in Promotion of Any Drug

Figure 7. Payments to physicians from pharmaceutical firms with drugs reaching patent expiry in 2015

Notes: Figures show the number of in-sample physicians who receive payments from the two pharmaceutical firms with drugs that go off patent in 2015. The left panel shows the number of physicians receiving payments made in promotion with the focal atypical antipsychotic. The right panel shows payments associated with any drug from that pharmaceutical firm.

Table IX shows the average payment amounts made by each focal pharmaceutical firm, both payments made in promotion of one of the five focal drugs and payments made in promotion of any drug. As expected, we see larger pharmaceutical firms provide payments to a higher percentage of physicians when measuring payment as from any firm. Smaller pharmaceutical firms more focused on mental health pharmaceuticals provide payments to a higher percentage of physicians who receive payments when only considering payments in promotion of a focal drug.

When looking at payments made for focal drugs, Otsuka, the manufacturer of Abilify, provides payments to 76 percent of the physicians who receive a payment. Payments from

TABLE IX

OPEN PAYMENTS SUMMARY STATISTICS

	Payment for focal drug			Payment for any drug		
	Receives payments	Amount		Receives payments	Amount	
		Mean (SD)	Median		Mean (SD)	Median
All firms	1%	498.10 (3665.24)	87.86	23%	92.78 (900.19)	19.93
Of those who receive any payment:						
AstraZeneca	45%	698.10 (4788.71)	63.98	56%	72.09 (442.66)	15.15
Eli Lilly & Company	1%	88.59 (83.29)	99.87	2%	73.95 (407.48)	12.67
Janssen	28%	486.90 (3073.90)	69.00	3%	128.45 (667.17)	13.84
Otsuka	76%	285.42 (1191.64)	111.75	59%	143.57 (637.21)	17.17
Pfizer	2%	374.95 (731.81)	11.68	13%	43.13 (326.66)	10.78

Notes: This table reports on the firms who made payments to physicians. Payment data are from CMS Open Payments. The first panel reports payments made in promotion of one of the five focal drugs, while the second panel reports payments made by each firm in promotion of any drug. The first column in each panel reports the percent of physicians in the sample receiving payments from each firm, conditional on any payment receipt. The second column reports the mean payment amount and standard deviation. The third column reports the median payment amount.

AstraZeneca are, on average, the most generous of the pharmaceutical firms. AstraZeneca, the manufacturer of Seroquel, provides payments to 45 percent of the physicians who receive payments. Eli Lilly and Pfizer both have drugs that go off patent early in the time period, contributing to a low percentage of payments made.

Payments made in promotion of any drug are more common, with 23 percent of physicians in the sample receiving a payment from at least one of the five focal pharmaceutical firms. Otsuka still provides payments to almost 60 percent of the physicians in my sample and are the most generous of the pharmaceutical firms, though the median payment amount is only $17.17. Pfizer and AstraZeneca now provide payments to a larger share of physicians when payment receipt is measured as payments made in promotion of any drug.

Due to measurement error and issues of endogeneity surrounding how pharmaceutical firms target physicians for marketing, the coefficients presented represent correlations between payment receipt and generic prescribing. Table X includes an indicator for payment receipt in promotion of one of the five focal drugs. Only one percent of physicians receive such payments, so there is little variation. Payment receipt is not associated with changes in generic drug prescribing.

Receiving any payment from a focal pharmaceutical firm is associated with decreased generic drug prescribing. Table XI, Panel A, Column 2 reports results for physician inertia using $Familiar_{ik}$ defined as drug class-familiarity. Class-familiar physicians are 2.5 percentage points less likely to prescribe the generic once it is available. Physicians who receive payments from pharmaceutical firms are 5.2 percentage points less likely to prescribe the generic once it is available. I then define $Familiar_{ik}$ as physicians who prescribed the brand equivalent before generic entry. Table XI, Panel B, Column 2 shows the effect for molecule-familiar physicians. Physicians with molecule familiarity are 2.5 percentage points less likely to prescribe the generic

once it is available. Again, physicians who receive payments from pharmaceutical firms are 5.3 percentage points less likely to prescribe the generic once it is available.

In summary, the results in Table X and Table XI present correlations between physician-industry interactions and generic utilization. Payments made in promotion of one of the five focal drugs appear to have little effect, though this is due to the lack of variation in payment receipt. Table XI shows a large, significant, negative association between payments and the probability of prescribing a generic drug. Controlling for all payment from a pharmaceutical firm reduces the inertia physician inertia effect, suggesting that my main results are downward biased. However, as shown in the right panel of Figure 7 and Table IX, these payments are measured with noise. Additionally, the results presented here are merely corollary, as physician-industry interactions are endogenous. Such interactions are the subject of further research in which I explore how physician-industry interactions alter physician search costs for insulin drugs, a class that does not face generic competition.

2.5.5 Variation in generic substitution laws

Generic substitution laws vary at the state level. They may be permissive and suggest that pharmacists recommend patients switch to the lower-cost alternative, or mandatory and require for pharmacists to switch patients to the generic version. Generic substitution laws may also vary on the level of consent required of the patient. Eight of the ten states have explicit generic substitution laws, where pharmacists may switch the patient to the generic version of the drug after receiving explicit patient consent. However, two states—Tennessee and Wyoming—have presumed consent laws, where pharmacists can presume that the patient

has consented to the generic version of the drug. In my sample, all states but one have permissive generic substitution, whereas Wyoming has mandatory substitution, where the pharmacist is required to switch the patient to the generic. Unfortunately, there are not enough prescriptions in Wyoming to tease apart the effects of mandatory and permissive generic substitution laws, though mandatory substitution laws have no significant effect on generic utilization in the literature (65).

Once the generic is available, generic utilization rates in presumed and explicit consent states are about equivalent. The generic utilization rate is 78 percent in explicit consent states and 76 percent in the two presumed consent states—the difference in generic utilization is not statistically significant. States requiring explicit consent have higher generic utilization rates than states with presumed patient consent. This suggests that the laws are not binding, and indeed, both patients and physicians can override generic substitution, even in states with mandatory substitution laws and presumed consent.

Table XII and Table XIII stratify the sample by states with presumed consent and states with explicit consent. In presumed consent states (Table XII), patient familiarity with both the drug class and molecule plays a larger role in generic utilization than in explicit consent states (Table XIII). However, the patient familiarity effect is insignificant across most specifications. The more negative point estimates on physician familiarity in presumed consent states than explicit consent states may due to physicians in presumed consent states being more likely to override a substitution. The results are at odds with the literature that finds presumed consent laws increase generic utilization (65; 62). However, the literature does not address inertia and

it may be that physicians unfamiliar with the choice set are driving the increase in generic utilization found in the literature as a result of presumed consent laws. Comparing raw means, it appears as though this is the case—in states with presumed consent, the generic utilization rate is 79 percent among physicians unfamiliar with the choice set, whereas drug class-familiar physicians have a generic rate of only 68 percent. My results exploring variation in generic substitution laws suggests that presumed consent laws do not decrease physician or patient inertia.

TABLE X

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—PAYMENT RECEIPT IN PROMOTION OF FOCAL DRUG

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Panel A: Familiarity with drug class before generic entry				
Class-familiar patient	-0.0115*		0.0041	-0.0040
	(0.0055)		(0.0061)	(0.0075)
Class-familiar physician		-0.0371***	-0.0389***	-0.0494***
		(0.0057)	(0.0063)	(0.0085)
Receives payment	-0.0022	0.0023	0.0020	0.0016
	(0.0176)	(0.0178)	(0.0178)	(0.0178)
Class-familiar physician				0.0216
× Class-familiar patient				(0.0116)
Adjusted R^2	0.081	0.082	0.082	0.082
Observations	36769	36769	36769	36769
Panel B: Familiarity with drug molecule before generic entry				
Molecule-familiar patient	-0.0180**		-0.0017	-0.0113
	(0.0057)		(0.0065)	(0.0076)
Molecule-familiar physician		-0.0351***	-0.0342**	-0.0544**
		(0.0061)	(0.0071)	(0.0109)
Receives payment	-0.0015	0.0032	0.0032	0.0027
	(0.0176)	(0.0177)	(0.0177)	(0.0178)
Molecule-familiar physician				0.0334*
× Molecule-familiar patient				(0.0136)
Adjusted R^2	0.081	0.082	0.082	0.082
Observations	36769	36769	36769	36769

Notes: Table shows the results from Equation 2.1. Observations are at the prescription level. Receives payment is an indicator equal to one if the physician received payment in promotion of the focal drug. All regressions include a vector of physician characteristics X_k, patient characteristics X_i, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

TABLE XI

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—PAYMENT RECEIPT IN PROMOTION OF ANY DRUG FROM FOCAL PHARMACEUTICAL FIRM

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Panel A: Familiarity with drug class before generic entry				
Class-familiar patient	-0.0146**		-0.0046	-0.0092
	(0.0055)		(0.0061)	(0.0076)
Class-familiar physician		-0.0252***	-0.0232***	-0.0294**
		(0.0057)	(0.0063)	(0.0084)
Receives payment	-0.0538***	-0.0523***	-0.0523***	-0.0521***
	(0.0050)	(0.0051)	(0.0051)	(0.0051)
Class-familiar physician × Class-familiar patient				0.0125
				(0.0116)
Adjusted R^2	0.084	0.084	0.084	0.084
Observations	36766	36766	36766	36766
Panel B: Familiarity with drug molecule before generic entry				
Molecule-familiar patient	-0.0204***		-0.0114	-0.0175*
	(0.0056)		(0.0066)	(0.0077)
Molecule-familiar physician		-0.0250***	-0.0189**	-0.0320**
		(0.0060)	(0.0070)	(0.0107)
Receives payment	-0.0536***	-0.0526***	-0.0527***	-0.0523***
	(0.0050)	(0.0051)	(0.0051)	(0.0051)
Molecule-familiar physician × Molecule-familiar patient				0.0214
				(0.0135)
Adjusted R^2	0.084	0.084	0.084	0.084
Observations	36766	36766	36766	36766

Notes: Table shows the results from Equation 2.1. Observations are at the prescription level. Receives payment is an indicator equal to one if the physician received payment in promotion of any drug from the pharmaceutical firm. All regressions include a vector of physician characteristics X_k, patient characteristics X_i, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

TABLE XII

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—PRESUMED CONSENT STATE-LEVEL GENERIC SUBSTITUTION LAWS

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Panel A: Familiarity with drug class before generic entry				
Familiar patient	-0.0301		-0.0085	0.0356
	(0.0268)		(0.0203)	(0.0333)
Familiar physician		-0.0467	-0.0414	0.151**
		(0.0300)	(0.0338)	(0.0551)
Familiar physician × Familiar patient				-0.2560***
				(0.0676)
Adjusted R^2	0.184	0.185	0.184	0.189
Observations	2021	2021	2021	2021
Panel B: Familiarity with drug molecule before generic entry				
Familiar patient	-0.0533*		-0.0237	-0.0023
	(0.0266)		(0.0330)	(0.0347)
Familiar physician		-0.0683*	-0.0516	0.1060
		(0.0308)	(0.0382)	(0.0860)
Familiar physician × Familiar patient				-0.1900*
				(0.0958)
Adjusted R^2	0.185	0.186	0.186	0.187
Observations	2021	2021	2021	2021

Notes: Table shows the results from Equation 2.1. Observations are at the prescription level. The sample is limited to prescriptions filled in states with presumed consent laws (Tennessee and Wyoming). All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, and month-since-generic-entry, month-year, state, plan type, and drug molecule fixed effects. Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

TABLE XIII

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—EXPLICIT CONSENT STATE-LEVEL GENERIC SUBSTITUTION LAWS

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Panel A: Familiarity with drug class before generic entry				
Familiar patient	-0.0065		0.0078	-0.0036
	(0.0057)		(0.0063)	(0.0077)
Familiar physician	-0.0312***	-0.0345***	-0.0488***	
	(0.0058)	(0.0064)	(0.0086)	
Familiar physician × Familiar patient				0.0299*
				(0.0118)
Adjusted R^2	0.083	0.083	0.083	0.084
Observations	34748	34748	34748	34748
Panel B: Familiarity with drug molecule before generic entry				
Familiar patient	-0.0111		0.0023	-0.0093
	(0.0058)		(0.0067)	(0.0078)
Familiar physician	-0.0274***	-0.0285***	-0.0520***	
		(0.0062)	(0.0072)	(0.0110)
Familiar physician × Familiar patient				0.0394**
				(0.0138)
Adjusted R^2	0.083	0.083	0.083	0.083
Observations	34748	34748	34748	34748

Notes: Table shows the results from Equation 2.1. Observations are at the prescription level. The sample is limited to prescriptions filled in states with explicit consent laws (Arkansas, Delaware, Illinois, Missouri, Oklahoma, Pennsylvania, Texas, and Wisconsin). All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, and month-since-generic-entry, month-year, state, plan type, and drug molecule fixed effects. Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

CHAPTER 3

IDENTIFYING MECHANISMS OF INERTIA: A STRUCTURAL APPROACH

The analysis in the previous section shows that choice persistence exists in physician prescribing behavior; however, it fails to control for unobserved persistence preference heterogeneity. In this section I establish a demand model for atypical antipsychotics, where the physician is the primary decision maker, to estimate parameters for switching costs and learning separately from unobserved preference heterogeneity. This framework allows me to quantify both switching costs and learning and to determine the welfare effects of counterfactual policies that may reduce inertia and improve welfare.

Physician inertia in prescribing behavior can be driven by a number of mechanisms: switching costs, learning, and search costs.[1] Search costs come from individuals needing to recall or specifically locate products to purchase them. In this setting, physician search costs for atypical antipsychotics are virtually nonexistent. Generic drugs may differ from brand-name drugs in additive ingredients, but the active molecule is identical. By the time of patent expiry for the focal drugs, the atypical antipsychotics drug class has been in use for about two decades. The focal drugs are approved for the treatment of many mental health disorders and were widely

[1]See (47), online Appendix D of (30), and (7) for more thorough discussions of possible mechanisms and micro-foundations of inertia.

prescribed and often the top selling drugs in the years prior to their loss of exclusivity. For example, Abilify came to the market in 2002. By 2015 when Abilify's patent expires, physicians who are prescribing the drug are by now familiar with the molecule.

3.1 A Demand Model for Atypical Antipsychotics

When physicians begin prescribing, they are aware of certain qualities of both their patients and the drug choices available to them. This includes their patients' diagnoses and some qualities of the available drugs (e.g., known side-effect profiles, patients' experiences with the drug, etc.). Physicians may be made aware of these qualities through past experience prescribing the drug, spillover effects from their colleagues, or interactions with the pharmaceutical industry which may provide some information about the drug's qualities.

Physicians may also prescribe a drug because physicians are inertial in their prescribing behavior. Inertial prescribing behavior can occur as a result of switching costs or learning by the physician. Switching costs are real or perceived costs to changing the product used. Implicit costs, such as risk-aversion and uncertainty, play a large role in switching costs. In this setting, physicians may experience a switching cost to changing their patients' drugs due to concerns about medication non-adherence. Learning occurs when physicians have imperfect knowledge about the quality of drugs, for which they gather information by prescribing across their patients. As physicians increase their prescriptions of a drug, they are able to update their beliefs about drugs' qualities, and become less inertial. The distinction between the source of choice persistence has important welfare implications. Finding that physicians experience switching costs may suggest that investments in interventions to make physicians less inertial

will be beneficial. However, if physicians' choice persistence is a function of the time it takes to learn, these investments may not be worthwhile if physicians make the welfare-enhancing choice eventually.

I consider the drug choice at the physician level. I assume physicians are at least partially altruistic and consider both patient health and the externality of their behavior on their patients' out-of-pocket pharmaceutical spending.[1] The physician considers past experiences with drugs (either their own in prescribing, or on behalf of their patient), their demographic information, relationships with pharmaceutical firms, as well as the copayment paid by the patient for the drug. Generally, physician i at time t receives the following utility from choosing drug j for patient k:

$$U_{ijt} = f(X_{it}, Z_{kt}, D_{jt}, p_{ikjt}, \xi_j, \theta) + \epsilon_{ijt}, \tag{3.1}$$

where f is a function, X_{it} are the characteristics of physicians, Z_{kt} are the characteristics of patients, D_{jt} are characteristics of drugs, and p_{ikjt} is the copayment paid by a patient for drug j. ξ_j are unobserved drug characteristics, θ are parameters that reflect preferences, and ϵ_{ijt} is an i.i.d. error term that is Type 1 Extreme Value distributed.

I adapt the framework presented in Equation 3.1 to a model of physician demand for atypical antipsychotics, estimated using a random coefficients mixed logit model to absorb any

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[1]Models of physician agency and shared decision-making with patients are discussed in (8) and (26). (37) considers an altruistic model where the physician internalizes patient utility due to pecuniary incentives and altruistic considerations.

unobserved persistent preference heterogeneity. Documenting inertia in longitudinal data is difficult as we must separate "structural" state dependence from "spurious" state dependence, or unobserved individual heterogeneity (31; 33; 32; 34; 22). (31) describes two reasons that current choices are correlated with past choices. First, previous choices have a causal effect on current choices, altering preferences, prices, or constraints relevant to future choices. Alternatively, individuals may differ on certain, serially correlated unobservables that may influence the probability they make a certain choice, but that are not influenced by previous choices. If these unobservables are correlated over time and left unaccounted for, previous choices will appear to be a determinant of future choices only due to these persistent preferences. Under structural state dependence, previous prescribing decisions have a causal impact on the current decision. However, under spurious state dependence, physicians exhibit strong and persistent, latent preferences for a brand-name drug. The model assumes a parametric distribution for the unobserved preference heterogeneity (the "random effect") to ensure the structural inertia parameters are uncorrelated with an individual-specific preference parameter. Separately identifying state dependence and unobserved persistent individual heterogeneity in this fashion has become common in the health industrial organization literature, focusing primarily on consumer plan choice and decision-making. (30) identifies inertia using new user choice in health insurance plan choice. This work has been followed by a literature on Medicare Part D plan choice, notably (55), (36), and (38). To distinguish between mechanisms of inertia, I include parameters for both switching costs and learning.

Physician prescribing behavior may differ on a variety of dimensions. I consider the physician's speciality, characteristics of their practice, and the physician's relationship with pharmaceutical companies as measured by payment receipt from drug manufacturers. To account for differences in prescribing behavior across patients, I also consider patient age, gender, and diagnoses.

The choice set faced by physicians changes as generic drugs enter the market. In January 2012, the choice set begins with five brand-name drugs. Generic drug entry serves as an exogenous shock to the choice set, which expands in the month the generic drug becomes available. By August 2015, the choice set has increased to ten drugs. Table I provides the five brand-name drugs and the dates of generic entry.

Using physician characteristics, I incorporate physician heterogeneity through the functional form of function f where physician characteristics are interacted with drug characteristics. The model presented below adapts the learning model in (22). My basic model has physician i make a drug choice for patient k from the choice set available at time t based on utility from choosing drug j:

$$u_{ijt} = -\alpha_k p_{ikjt} + \gamma_{1i}\mathbb{I}\{s^j_{t-1} = j\} + \gamma_{2i}\mathbb{I}\{s^m_{t-1} = m\} + \pi_{1i}\mathbb{I}\{s^j_{t-1} = j\} \cdot E_{ijt} + \pi_{2i}\mathbb{I}\{s^m_{t-1} = m\} \cdot E_{ijt} + \beta_i D_{jt} + \epsilon_{ijt}, \quad (3.2)$$

where ϵ_{ijt} is the standard logit i.i.d. Type 1 Extreme Value error term. p_{ikjt} is the copayment amount paid by physician i's patient k for drug j at time t. For each drug choice available to

the physician, I use the inferred copay regime and formulary to determine the copay a patient on each pharmaceutical plan would face for each drug. I assume that physicians are myopic and make decisions based on the price the patient would face at time t. Physicians are not forward-looking and do not consider a patient's out-of-pocket maximums or deductible levels over the course of the year when making a drug choice at time t. See 3.2 for tests of this assumption. α_k then reflects the marginal utility of wealth for patients, which is internalized by the partially altruistic physician.

Physician switching costs are represented by $s^j_{t-1} \in \{1, ..., J\}$ and $s^m_{t-1} \in \{1, ..., M\}$, which summarizes the history of past prescribing behavior, within and across molecules, respectively. Across molecule switching costs have an indicator equal to one if $\{s^m_{t-1} = m\}$, or the molecule prescribed in this period is the same as the previously prescribed molecule. Within molecule switching costs have an indicator equal to one if $\{s^j_{t-1} = j\}$ and the generic version of m is available at time t. E_{ijt} represents the cumulative number of times the physician has previously prescribed a drug. D_{jt} is a vector of drug fixed effects.

I model persistent, unobserved preference heterogeneity by including normally distributed random coefficients on the drug fixed effects. This absorbs any unobserved preference heterogeneity for each specific drug. Formally, this is represented by

$$\beta_i = \sum \beta X_i + \nu_i \tag{3.3}$$

where $\nu_i \sim N$ represents idiosyncratic preferences for the drug. X_i is a vector of observed attributes for the physician i, including physician gender, indicators for the top three most common specialties in my sample data,[1] practice size, number of years in practice, and if the physician uses an EHR. I also include an indicator for whether the physician received payment in promotion of the focal drug from the pharmaceutical firm which manufacturers the drug.

Switching costs are represented by γ_1 and γ_2. If γ is greater than zero, then the model predicts that physicians have switching costs in prescribing. γ_1 reflects switching costs between brand and generic versions of $j \in m$, whereas γ_2 reflects switching costs between molecules. Learning is represented by π_1 and π_2. If learning occurs, the interaction should decrease switching costs as prescribing experience with drug j accumulates, so π is less than zero. π_1 reflect within-molecule learning, so learning about the generic, whereas π_2 reflects across molecule learning. π_2 can help us to understand the level of experimentation that occurs across molecules.

3.2 Identification

Coefficients are identified by leveraging over time correlation in prescriptions within a physician. Identification of the switching costs coefficients, γ, relies on certain conditions to be true. The first issue to consider is distinguishing between "spurious" and "structural" state-dependence. The inclusion of random coefficients in the model absorb the unobserved individual heterogeneity, in a way that is consistent in the literature. The assumption is that the ran-

[1]These specialities are family medicine, internal medicine, and psychology.

dom coefficients capture individual-specific unobserved persistence in preferences, while γ, the switching costs parameters, and π, the learning parameters, capture the structural inertia.

The second condition is that the choice set changes over the time period. In this setting, changes to the choice set over time are prompted by generic drug entry. One such change is the entry of new drugs. Generic drug entry also leads to changes in price (copay amounts) for the drugs within the choice set. When the generic drug enters, the insurer moves the brand-name drug into a more expensive tier of the formulary. Both the number of choices and the utility of choices changes considerably over time. Without these changes, the environment would be stable and we would not expect to observe changes in choices, with or without inertia.[1]

The third condition is being able to identify an active choice for each physician. A data shortcoming is that I do not have a full prescribing history for physicians, and therefore cannot observe a physician's first prescription of the drug class. The initial conditions problem, described by (32) may be present. Other recent papers that make use of similar models observe an active or first choice for all individuals in their data (30; 55). To attempt to solve this problem, I limit observations physicians who are class-unfamiliar in March 2012.[2] I cannot fully separate inertia from unobserved persistent preference heterogeneity from true inertia, as I do not know the true correlation between a physician's first choice and unobservable preferences. Therefore,

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[1]Figure 12, Appendix A shows how changes to the choice set affect changes in prescribing. The figure plots physician switching rates within and across molecules over time. The vertical lines indicate months of generic entry. Immediately following generic entry, there is a large increase in switching within molecule, from the brand to generic drug. Across molecule switching is relatively stable over time.

[2]I.e., the drug class-unfamiliar physicians for Geodon and Seroquel from the reduced form exercise.

γ_2, across molecule switching costs, likely reflects persistence preference heterogeneity in addition to structural inertia. γ_1 is better identified since I observe when the generic versions enter the choice set.

I also assume that physicians are myopic. The return to learning, and thus experimentation, is higher for physicians who expect to prescribe additional antipsychotics in the future. A forward-looking physician will be more likely to try the generic drug or experiment with different antipsychotic molecules, whereas a myopic physician will be indifferent between the brand and generic versions of the molecule, and be less likely to experiment.

First, I show that switching rates do not vary across physicians who will see many patients in the future and those who do not. Table XIV reports within and across molecule switch rates for all physicians. The average physician switches across molecules for 11 percent of prescriptions and switches within molecules for about 3 percent of prescriptions. For physicians expecting to have a high inflow of patients—four or more patients in the next year—the switching rates are the same. Switching rates are also similar for physicians expecting to have a low inflow—one or fewer patients—in the next year.

I then test whether physicians' probability of prescribing the generic responds to the likelihood they will treat new patients requiring antipsychotics in the future. This test follows from (28). Table XV shows that familiar physicians with a higher number of future patients are *less* likely to experiment with using the generic version following generic entry than physicians with low inflows. The results imply that physicians with higher future inflows exhibit more choice persistence toward the brand-name drug in their prescribing behavior. The results suggest that

TABLE XIV

PHYSICIAN SWITCHING RATES BY NUMBER OF FUTURE PATIENTS

	(1) All physicians	(2) High inflow	(3) Low inflow	(5) Psychiatrists	(5) Other specialists
Within molecule	2.77%	2.78%	2.77%	2.73%	2.77%
	(2.05%)	(2.13%)	(2.06%)	(2.06%)	(2.05%)
Across molecule	11.45%	11.35%	11.46%	11.48%	11.45%
	(1.63%)	(1.72%)	(1.63%)	(1.70%)	(1.62%)
Observations	46482	3807	38777	8487	37995

Notes: Table shows switching rates by the number of future patients for physicians. High inflow physicians will treat 4 or more patients with an atypical antipsychotic in the next year, whereas low inflow physicians will treat 1 or fewer patients in the next year. Observations are at the prescription level. Standard deviation in parentheses.

physicians are not forward-looking when it comes to their prescribing behavior. Physicians with high future patient inflows are more likely to benefit from experimentation; however, I do not observe these physicians switching within or across molecules more than their peers, nor do I observe them exhibiting less inertia. It therefore seems reasonable to assume that physicians are myopic.

Identification of the demand model is similar to the methods used by (30), (55), and (38). The mixed logit model with random coefficients described in Equation 3.2 is estimated using a simulated maximum likelihood approach as described in (68) and (39).

TABLE XV

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—RESPONSE TO FUTURE PATIENT LEVELS

	Familiarity with drug class	Familiarity with molecule
	(1) Generic	(2) Generic
Familiar physician	-0.0406	0.0027
	(0.0243)	(0.0279)
Familiar physician × high inflow	-0.0618*	-0.0699
	(0.0312)	(0.0365)
Familiar physician × low inflow	0.0251	-0.0264
	(0.0252)	(0.0292)
Adjusted R^2	0.060	0.059
Observations	19171	19171

Notes: Table shows the results from Equation 2.1, with interactions for future patient inflows. High inflow physicians will treat 4 or more patients with an atypical antipsychotic in the next year, whereas low inflow physicians will treat 1 or fewer patients in the next year. Observations are at the prescription level, limited to the first ten prescriptions written by a physician to show how initial choices respond to future patient inflows. All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, plan type fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

3.3 Results

Table XVI presents results. Physician heterogeneity enters through interactions with switching costs and learning. Patient heterogeneity enters the model through interactions with co-payment, switching costs, and learning.[1]

[1]Table XXIV, Appendix A shows results for the primary coefficients with different levels of heterogeneity.

There is limited unobserved heterogeneity in preferences for drugs. For example, the standard deviation in the valuation of Abilify is $80 relative to the mean of $318. Seroquel has the largest amount of unobserved preference heterogeneity, with a standard deviation of 100% the mean.

The average price coefficient (α_k) is small, but highly significant. The size of α is not unexpected, given that prices are paid by patients with health insurance coverage—the price they face is due to cost-sharing and much lower than the listed drug price. Own-price elasticity is given by:

$$\varepsilon_{jp_{ikjt}} = \alpha_k p_{ikjt} \cdot \frac{\exp(\delta_{ikjt})}{\sum \exp(\delta_{ikjt})}, \tag{3.4}$$

where δ_{ikjt} is the mean utility that physician i in period t receives from prescribing drug j to patient k. I find an average, own-price elasticity of -0.0007. In an analysis of drug class specific elasticities, (24) find that patients are price inelastic in their demand for atypical antipsychotics. My estimates reinforce that patients and their physicians are price inelastic with respect to atypical antipsychotic drugs. In general, patients exhibit a relatively low elasticity for pharmaceuticals in part due to insurance cost-sharing incentives. In a model of physician choice, (29) identify an own-price elasticity of -0.06 for statins, using the negotiated point-of-sale price under Medicare Part D scaled by a time- and market- varying cost-sharing parameter. (24) find an average price elasticity of -0.14 across all drug classes.

Switching costs are estimated to be substantial on average and are larger within molecule than across molecule, with physicians willing to pay $647 to keep their patient on the same drug versus $460 to keep their patient on the same molecule. The level of inertia varies across physician and patient characteristics. Psychiatrists have lower switching costs both within and across molecules, whereas the number of years a physician has been in practice reduces within-molecule switching costs and increases across molecule switching costs. A similar pattern exists for patients diagnosed with mood disorders, which include bipolar disorder. The large switching costs parameter reinforces that physicians are inertial in their prescribing of drugs across patients.

Learning is reflected in the parameters on the interaction of experience E_{ijt} and switching costs, π_1. Each additional prescription of a drug decreases within-molecule switching costs by $22, whereas additional prescriptions increase across molecule prescriptions by $171. Heterogeneity across prescribers and patients is particularly important for learning. The baseline coefficients for within and across molecule learning are similar in magnitude, though opposite signed, whereas the magnitudes of coefficients for the interactions with physician and patient characteristics differ dramatically.

TABLE XVI

PARAMETER ESTIMATES OF THE RANDOM COEFFICIENTS MIXED LOGIT CHOICE MODEL

Drug Characteristics	Mean WTP	Coeff.		Interactions with key demographics: Psychiatrist	Years practicing	Mood
Copayment amount	-$1	-0.005	(0.002)	–	–	0.002 (0.001)
Switching costs (within molecule)	$647	1.970	(0.233)	-0.08 (0.13)	-0.65 (0.45)	-0.69 (0.14)
Switching costs (across molecule)	$460	1.28	(0.19)	-1.09 (0.11)	1.05 (0.38)	0.38 (0.12)
$E_{ijt}\times$ Switching costs (within molecule)	-$22	-0.28	(0.05)	0.05 (0.03)	-0.07 (0.11)	0.13 (0.03)
$E_{ijt}\times$ Switching costs (across molecule)	$171	0.34	(0.04)	0.77 (0.03)	-0.48 (0.11)	-0.57 (0.03)
Random Parameter Statistics						
Abilify—μ	$318	1.78	(0.20)			
Abilify—σ	$80	0.45	(0.05)			
Geodon—μ	-$432	-2.42	(0.28)			
Geodon—σ	$238	1.33	(0.13)			
Invega—μ	-$341	-1.91	(0.27)			
Invega—σ	$291	-1.63	(0.12)			
Seroquel—μ	$116	0.65	(0.20)			
Seroquel–σ	$116	0.65	(0.05)			
Symbyax—μ	-$541	-3.03	(0.34)			
Symbyax—σ	$204	1.14	(0.19)			
Mean α_{ikjt}	-0.0056					
Mean $\varepsilon_{jp_{ikjt}}$	-0.0007					
Log-likelihood	-26,391					
Observations	383,447					
Number of prescriptions	45,259					

Notes: The table reports estimates of utility parameters from Equation 3.2. Willingness to pay is calculated by dividing all marginal utility coefficients by the price coefficient, α_{ikjt}. Psychiatrist is an indicator the physician is a psychiatrist. Years practicing is the cumulative number of years since a physician's date of medical school graduation. Mood is an indicator the patient is diagnosed with a mood disorder, which includes bipolar disorder. Only key coefficients are reported; generic drug fixed effects are not reported. Demographic interactions also include indicators for family medicine physicians and internal medicine physicians, EHR use, interactions with the pharmaceutical industry, physician gender, practice size, patient age, patient gender, and indicator variables for patient chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, personality disorders, and schizophrenia). Standard errors are in parentheses. Own-price elasticity, $\varepsilon_{jp_{ikjt}}$, is calculated from Equation 3.4.

CHAPTER 4

COUNTERFACTUAL SIMULATIONS AND WELFARE ANALYSIS

4.1 Welfare

To understand how prescribing behavior can impact physician and patient welfare, I explore several counterfactual scenarios that change the relative utility of the drugs available in the choice set. I first consider a counterfactual in which I remove switching costs within drug molecules. This counterfactual is intended to simulate policies that could decrease physician inertia toward the brand-name version, while still allowing for choice persistence between molecules.

I conduct other counterfactual simulations which model the influence that insurer incentives can have on prescribing practices. Specifically, I first consider an insurance policy in which brand-name drugs are removed from the formulary once the generic version becomes available. This counterfactual may also address the welfare effects of mandatory generic substitution laws, in which pharmacists are required to switch patients to generic versions of the drug. I also explore the change in welfare under an increase in the copay differential between brand-name and generic drugs. Since demand for atypical antipsychotics is relatively price inelastic, the salience of a larger copay differential may incentivize physicians to be swifter in switching their patients to generic drugs. I use the model presented in Table XVI for the counterfactual simulations.

To assess the change in physician welfare under the counterfactual simulations, I calculate measures of changes in consumer surplus. Formally, the change in expected consumer surplus for physician i treating patient k with utility parameters θ_i from a change in the characteristics of drugs in the choice set J:

$$\Delta E[CS_i|\theta_i] = \frac{1}{\alpha_{ikjt}}\Big[ln\big(\sum_{j\in J} exp(\delta'_{ikjt})\big) - ln\big(\sum_{j\in J} exp(\delta_{ikjt})\big)\Big], \tag{4.1}$$

where δ_{ijmt} is physician utility as described in Equation 3.2 less the unobserved portion ε and δ'_{ijmt} is the utility under the counterfactual.

The structure of the utility equation with its logit error term implies that removing drugs to the choice set, as in the second counterfactual, would underestimate welfare. To avoid this issue, I also consider the utility a physician gets from only the five drugs with the highest utility. Formally, this is given by:

$$\Delta E[CS_i|\theta_i] = \frac{1}{\alpha_{ikjt}}\Big[ln\big(\sum_{j\in J'}^{5} exp(\delta'_{ikjt})\big) - ln\big(\sum_{j\in J}^{5} exp(\delta_{ikjt})\big)\Big]. \tag{4.2}$$

By removing the availability of brand name drugs after generic entry, the choice set is decreased and the consumer surplus calculation presented in Equation 4.1 will allocate a lower welfare to prescriptions made in scenarios where the choice set is limited. The consumer surplus in

Equation 4.2 corrects for this by only considering the welfare a physician gets from the five drugs that provide the highest welfare.[1]

For each counterfactual, I also present the average copay amount and percent of prescriptions for generic drugs. These values are weighted by the probability of choosing a given drug, given by:

$$Pr_{ikjt} = \frac{\exp(\delta_{ikjt})}{\sum \exp(\delta_{ikjt})}. \tag{4.3}$$

4.2 Removal of Switching Costs

The first counterfactual shuts down the inertia channel by removing switching costs within drug molecules. This counterfactual is meant to apply broadly to policies that could decrease inertia, such as the provision of information on generic drug quality and patient copay differentials. It could further apply to an initiative on behalf of generic drug manufacturers to produce generic atypical antipsychotics that more closely resemble their brand-name counterparts (e.g., more similar in color, shape, size, etc.). This type of initiative may assuage physician concerns of medication non-adherence from switching their patients to the generic drug.

I set the within-molecule switching cost parameter γ_1 in the choice model equal to zero for all individuals. This considers the switching costs as a real cost. I then calculate the change in consumer surplus without this cost.

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[1]The idea here is similar to that of the "plan swapping" scenario in (18).

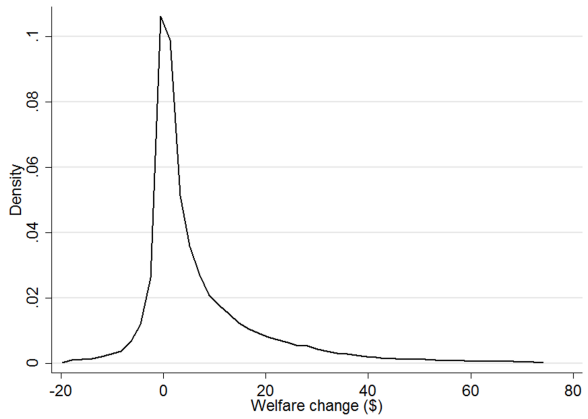
Table XVII summarizes the changes in consumer surplus for each counterfactual scenario. Physician welfare increases $7 on average per prescription when the within-molecule inertia channel is shut down. Just over 15 percent of physicians are better off when they are allowed to exhibit within-molecule switching costs. In the factual scenario, individuals pay an average copay of $34 and choose a generic drug 40 percent of the time. Removing switching costs increases physician welfare, but neither changes patients' out-of-pocket costs nor substantively change the drugs they are prescribed.

Figure 8 in the top left panel shows the change in welfare when switching costs are removed based on the consumer surplus calculation in Equation 4.1. Welfare is expressed in dollar units, based on the marginal utility of wealth derived from the mixed logit model with random coefficients in Table XVI.

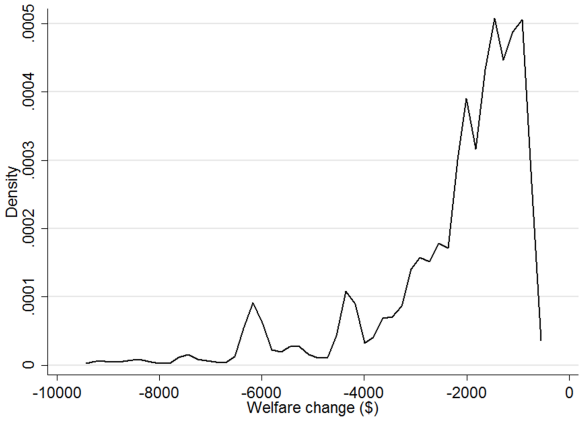
4.3 No Brand-Name Drugs

In this counterfactual, I remove brand-name drugs from the choice set after the generic is available. This simulation sheds light on two different policies. First, this counterfactual can demonstrate the effect of removing brand-name drugs from an insurer's formulary after generic entry. Also, removing brand-name drugs from the choice set can simulate the welfare effects of mandatory generic substitution laws. This counterfactual also removes within-molecule switching costs for physicians.

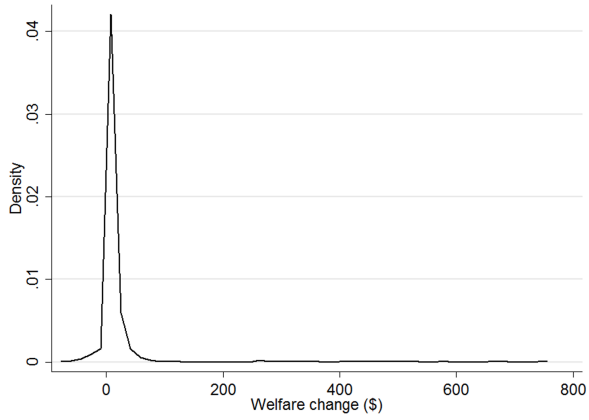
Currently, the insurer moves the brand-name drug into a higher formulary tier when the generic drug enters, making the copay for the brand-name drug more expensive. Figure 2 shows



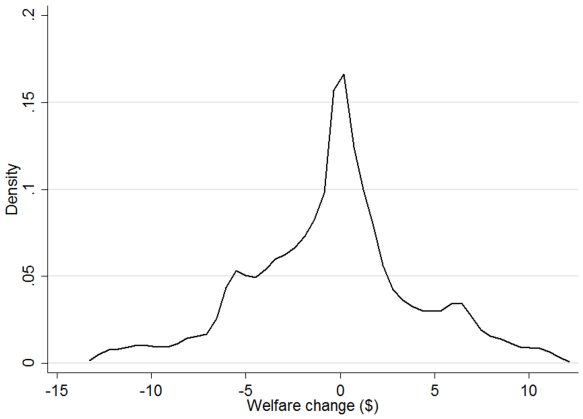
Counterfactual 1: Removal of Switching Costs



Counterfactual 2: No brand-name drugs



Counterfactual 2: No brand-name drugs (Top 5 utility drugs)



Counterfactual 3: Increase Copay Differential

Figure 8. Distribution of welfare gains under counterfactual scenarios

Notes: This figure plots the 1-99th percentile of the distribution of welfare gains for each counterfactual scenario.

TABLE XVII

COUNTERFACTUAL RESULTS WELFARE ANALYSIS

	Counterfactual 1	*Counterfactual 2*	*Counterfactual 3*
	No switching costs	No brand name drugs	Increased copay differential
Panel A: ΔCS from all available drugs			
Mean Welfare	7.28	-2330.87	6.48
Standard Deviation	16.19	1779.08	124.14
Median Welfare	2.34	-1801.65	-0.08
% Positive	74.14%	0%	46.60%
Average Copay Amount	33.63	28.15	58.91
% Choosing Generic	40.46%	64.47%	41.09%
Panel B: ΔCS from top 5 utility drugs			
Mean Welfare	6.98	31.15	1.74
Standard Deviation	15.78	156.28	67.10
Median Welfare	2.34	6.09	-0.13
% Positive	74.86%	92.48%	45.10%
Average Copay Amount	33.18	28.15	50.29
% Choosing Generic	45.22%	64.47%	49.72%

Notes: 45,259 observations (prescriptions). Percent positive is the percentage of individuals with a positive welfare change. Average copay amount is the average copay an individual pays in the counterfactual scenario weighted by the probability of selecting each drug. Percent choosing generic is the percentage of prescriptions written for a generic drug.

the changes in patient out-of-pocket expenses for different drugs over time. This counterfactual scenario removes the choice of the brand-name drug after the generic is available.

Using the consumer surplus calculation in Equation 4.1, welfare decreases by $1,802 at the median when brand-name drugs are not available. This welfare change is large, due to the logit error term and the removal of drug choice. Limiting the choice set will overestimate the loss

consumers face from decreased choice. Figure 8 (top right panel) shows the large distribution in welfare changes.

Using Equation 4.2, which corrects for the logit error term by taking into account only the 5 drugs that provide the most utility, physicians have welfare gains of $31 per prescription when brand-name drugs are not available. 92 percent of prescriptions have an increase in welfare. Patient copays decrease by $6 on average and 64 percent choose a generic drug. The bottom left panel of Figure 8 shows the distribution of welfare gains using Equation 4.2.

4.4 Increase Copay Differential

This counterfactual changes the copay differential between generic and brand-name drugs. Under the current insurer policy, the copay differential between brand and generic drugs is about $20 to $30, as shown in Figure 2. This counterfactual aims to address how copay regimes and formulary structure can be used to encourage additional generic use. For this counterfactual, I set all brand-name drug copays equal to $100 and all generic copays to zero.

Average physician welfare increases by $6 per prescription when the copay differential is increased, though welfare decreases by $0.08 for the median prescription. The distribution of welfare changes with an increased copay differential is plotted in the bottom right panel of Figure 8. About half of prescriptions experience a welfare gain under the counterfactual with increased copays. Patient copays increase to $59, suggesting that despite the higher copay, patients and physicians continue to choose the brand-name drug. The percent of prescriptions written for a generic drug is 41 percent, only one percentage point higher than the 40 percent that occurs in the factual scenario.

CHAPTER 5

CONCLUSION

5.1 Summary and Contributions

In this paper I explore physician prescribing behavior for five atypical antipsychotics as their generic counterparts become available. Generic drug use can lower pharmaceutical spending and so understanding prescribing patterns is valuable. In a quasi-experimental framework, I show that physicians are driving inertial behavior toward the brand-name drug, rather than their patients. I compare the likelihood of prescribing the generic drug once it becomes available for experienced physicians to those physicians who did not begin prescribing until after the generic has become available. I find that experienced physicians are about three percentage points less likely to prescribe the generic drug, which translates to a 16 percent increase in the utilization of brand-name drugs. Payment receipt from a pharmaceutical firm further reduces the likelihood the generic drug is prescribed. To find evidence of learning, I use an event study approach that allows the experienced physician effect to vary by the number of months the generic drug has been available. In the first month following generic entry, experienced physicians are less likely to prescribe the generic drug than newer physicians.

Having identified that inertia and learning exist, I develop a structural model for physician demand for atypical antipsychotics in light of the reduced-form evidence. To distinguish between mechanisms of inertia, I include parameters for switching costs and learning. Unobserved

persistent preference heterogeneity is modeled by including normally distributed random coefficients on drug fixed effects. Results show that physicians exhibit large switching costs which decrease as the generic drug becomes available. Experience prescribing the drug decreases switching costs, indicating that learning is present.

I use the model estimates to conduct counterfactual simulations and compare welfare under different policies. I first consider a counterfactual in which I remove switching costs. Average physician welfare increases by about $7 per prescription when there are no switching costs. Two counterfactual simulations model possible changes to insurer incentives. The first removes brand-name drugs from the choice set and shows physicians to be substantially worse off due to the decrease in choice. Controlling for the number of drugs in the choice set, physicians see a $31 increase in welfare per prescription on average. The second increases the copay differential between brand and generic drugs, increasing welfare by about $6 on average. Because patients are price-inelastic, changes to copayments do little to persuade patients and physicians toward the generic drug.

Dramatic changes to the copay differential did little to encourage generic drug use. When generic drugs enter, insurers update their drug formulary and usually put brand-name drugs in a higher tier with a higher copay. The counterfactual suggests that such policies by the insurer are not persuasive to patients and their physicians.

The counterfactual simulations imply that policies that decrease switching costs would be beneficial to both physicians and their patients. However, while removing brand-name drugs

from the choice set increased welfare and decreased patient copays, such a policy may actually result in adverse health events due to medication non-adherence.

5.2 Recommendations for Future Work

Future research will study the effects of switching to generic drugs on patient medication adherence and health outcomes in the context of antipsychotics, where drug adherence is particularly important.

Finally, physician-industry interactions play a significant role in prescribing behavior. I face limitations in the extensions of understanding payments in this paper due to the timing of generic entry and the availability of the Open Payments data. Better understanding how such interactions influence physician search costs and prescribing behavior is the subject of future research.

APPENDICES

Appendix A

SUPPLEMENTARY FIGURES AND TABLES

Appendix A (Continued)

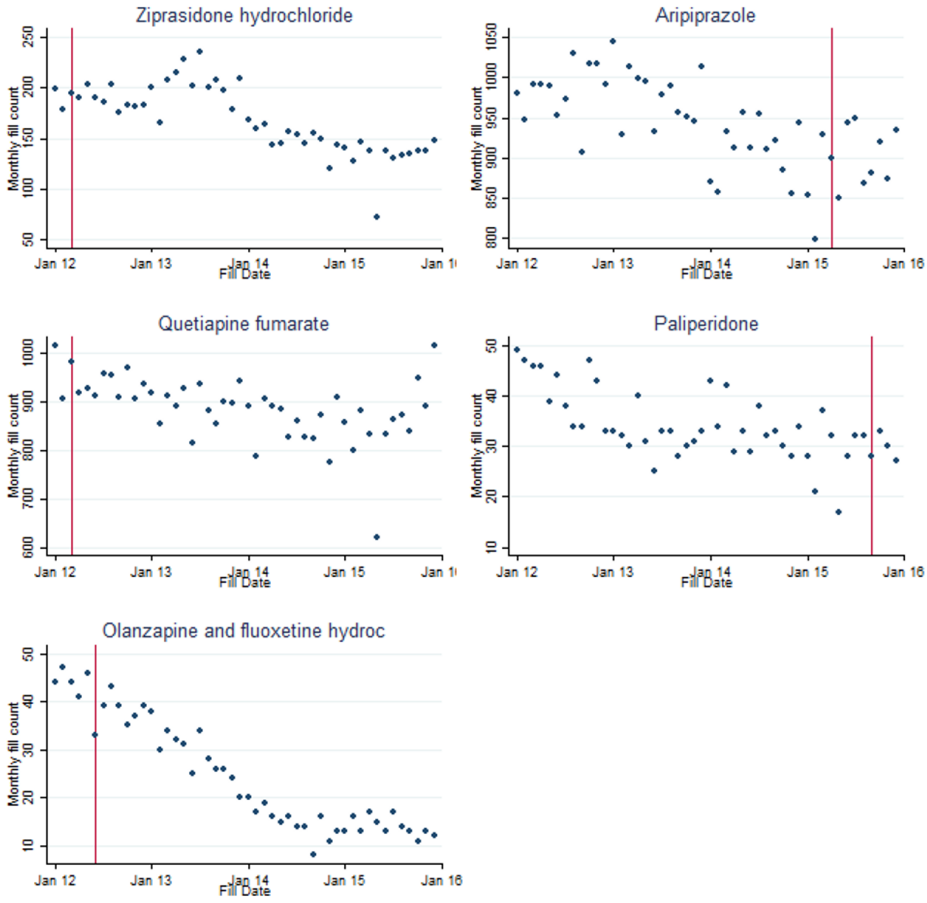
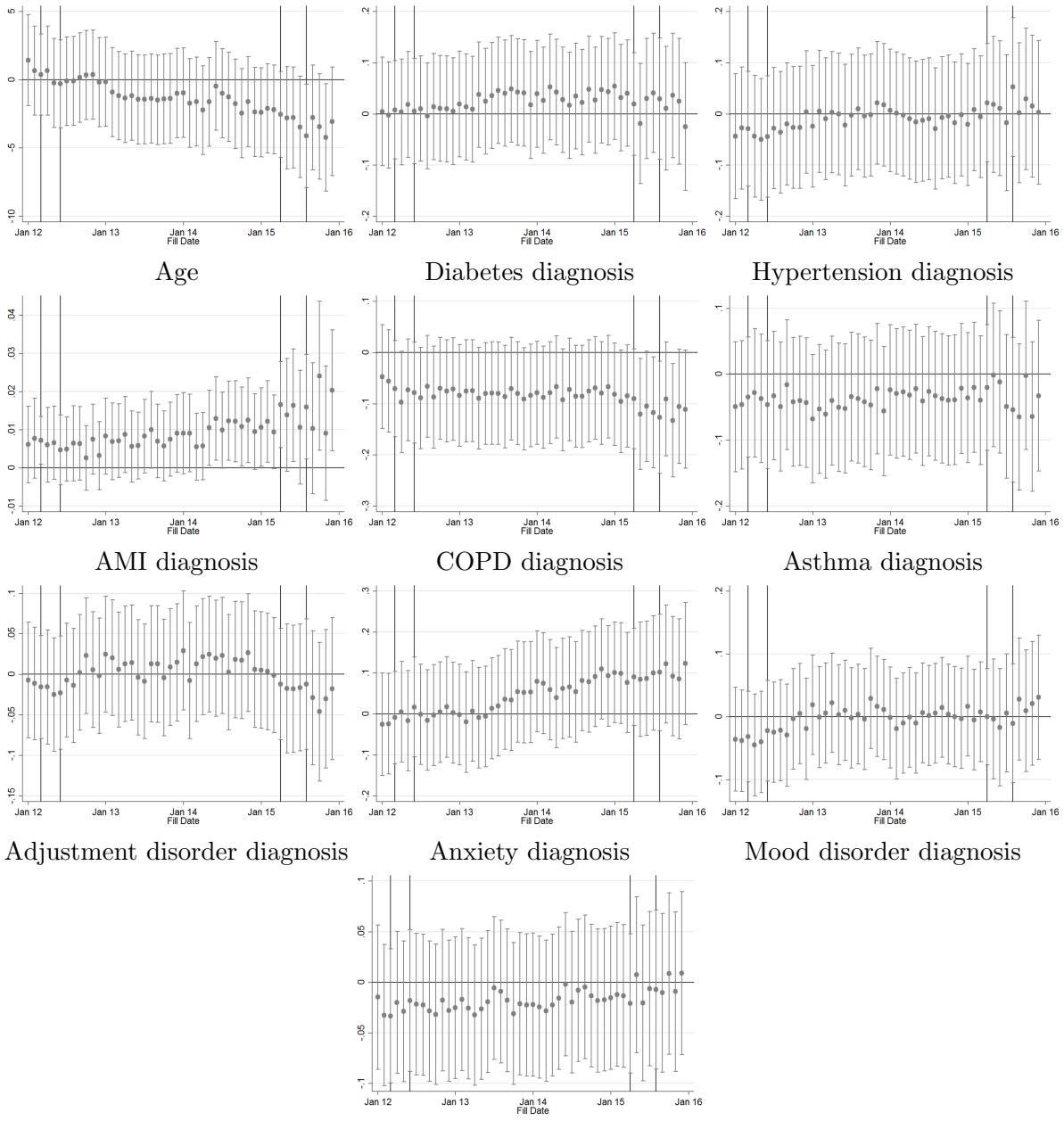


Figure 9. Monthly fills by molecule

Notes: This figure plots the total number of fills each month by molecule. The vertical line marks the month of generic entry for each drug molecule.

Appendix A (Continued)



Age | Diabetes diagnosis | Hypertension diagnosis

AMI diagnosis | COPD diagnosis | Asthma diagnosis

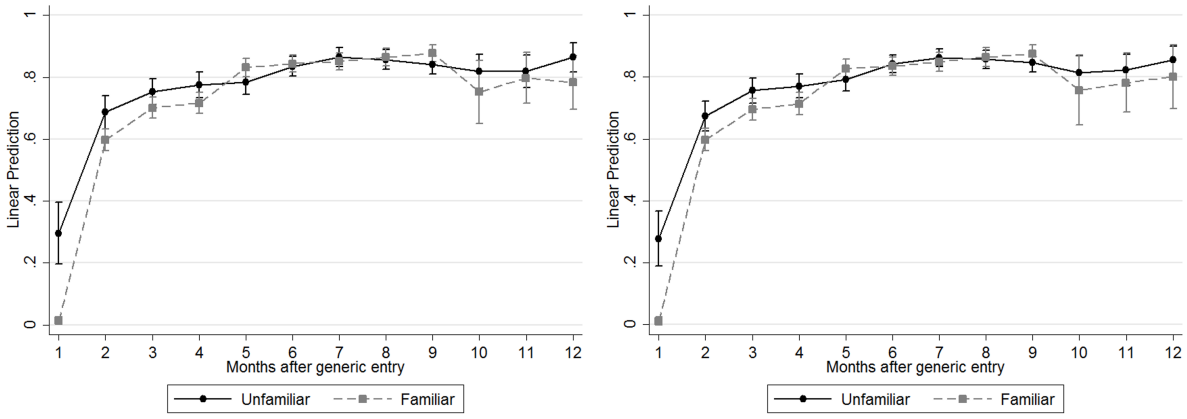
Adjustment disorder diagnosis | Anxiety diagnosis | Mood disorder diagnosis

Personality disorder diagnosis

Figure 10. Patient characteristics by physician familiarity over time

Notes: Figures plot the coefficient on the interaction of month-year fixed effects and the drug-class familiar physician indicator from a regression of patient characteristics on month-year fixed effects interacted with the drug-class familiar physician indicator, physician characteristics, remaining patient characteristics, and month-since-generic-entry, state, plan type, and drug molecule fixed effects.

Appendix A (Continued)



Drug Class Familiarity | Molecule Familiarity

Figure 11. Physician learning—excluding refills

Notes: Figures show the marginal effects and 95% confidence intervals for familiar and unfamiliar physicians from Equation 2.2. The left panel measures drug class familiarity. The right panel uses molecule familiarity. The sample excludes refills.

Appendix A (Continued)

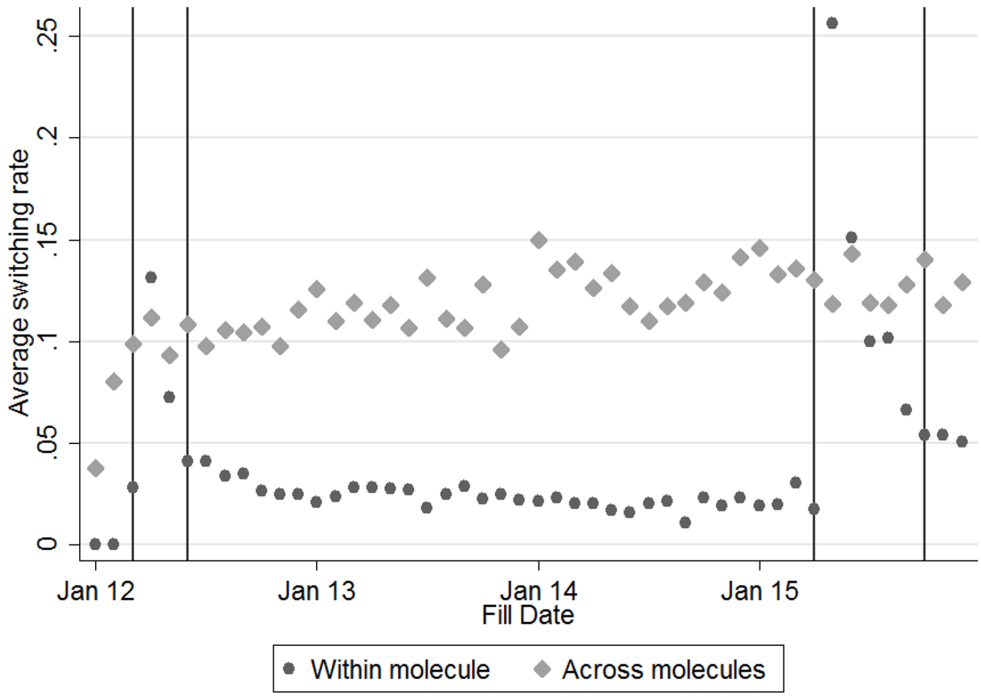


Figure 12. Physician drug switching within and across molecules

Notes: Figure shows physicians' average switching rate within and across drug molecules by month. The vertical lines indicates months of generic entry.

Appendix A (Continued)

TABLE XVIII

PATIENT CHARACTERISTICS BY FAMILIARITY—DIAGNOSED BEFORE GENERIC AVAILABLE

		Mental health diagnosis before generic available	
	All Mean/(SD)	Unfamiliar Mean/(SD)	Familiar Mean/(SD)
Number of fills	6.95	6.33	7.99
	(8.75)	(8.09)	(9.68)
Number of physicians	1.89	1.82	2.06
	(1.46)	(1.37)	(1.61)
Age	40.85	41.13	40.25
	(15.67)	(15.42)	(15.89)
Female	0.61	0.58	0.63
	(0.49)	(0.49)	(0.48)
Chronic condition diagnoses			
Diabetes	0.17	0.17	0.17
	(0.37)	(0.37)	(0.37)
Hypertension	0.30	0.31	0.30
	(0.46)	(0.46)	(0.46)
AMI	0.01	0.01	0.01
	(0.08)	(0.08)	(0.08)
COPD	0.11	0.11	0.11
	(0.31)	(0.31)	(0.32))
Asthma	0.13	0.13	0.14
	(0.34)	(0.34)	(0.34)
Mental health diagnoses			
Adjustment	0.13	0.11	0.15
	(0.34)	(0.31)	(0.36)
Anxiety	0.60	0.58	0.64
	(0.49)	(0.49)	(0.48)
Mood	0.84	0.75	0.92
	(0.37)	(0.43)	(0.28)
Personality	0.05	0.05	0.06
	(0.22)	(0.22)	(0.23)
Schizophrenia	0.11	0.11	0.13
	(0.31)	(0.32)	(0.33)
Observations	9064	3935	5781

Appendix A (Continued)

TABLE XIX

PHYSICIAN CHARACTERISTICS BY FAMILIARITY—PRACTICING BEFORE GENERIC AVAILABLE

		Practicing before generic available	
	All Mean/(SD)	Unfamiliar Mean/(SD)	Familiar Mean/(SD)
Number of prescriptions	4.96	3.61	5.80
	(7.91)	(4.89)	(9.46)
Number of patients	1.35	1.25	1.53
	(1.28)	(0.99)	(1.63)
Female	0.31	0.84	0.30
	(0.46)	(0.37)	(0.46)
Years in practice	22.64	1.82	22.86
	(10.85)	(0.70)	(10.69)
Practice size	199.21	346.88	199.70
	(393.51)	(700.13)	(392.10)
Uses EHR	0.45	0.04	0.45
	(0.50)	(0.19)	(0.50)
Receives payment	0.01	0.00	0.01
	(0.11)	(0.00)	(0.12)
Common Specialties			
Family medicine	0.24	0.04	0.24
	(0.43)	(0.19)	(0.43)
Psychiatry	0.10	0.03	0.12
	(0.30)	(0.16)	(0.32)
Internal medicine	0.15	0.05	0.15
	(0.36)	(0.22)	(0.36)
Observations	12692	80	14199

Appendix A (Continued)

TABLE XX

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION: PATIENTS DIAGNOSED AND PHYSICIANS PRACTICING BEFORE GENERIC ENTRY

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Familiar Patient	-0.0203***		-0.0204***	-0.0053
	(0.0053)		(0.0053)	(0.0645)
Familiar Physician		0.0449	0.0461	0.0529
		(0.0336)	(0.0335)	(0.0447)
Familiar Physician × Familiar Patient				-0.0152
				(0.0645)
Adjusted R^2	0.082	0.081	0.082	0.082
Observations	36769	36769	36769	36769

Notes: Table shows the results from Equation 2.1. Patients are familiar if they are diagnosed with a mental health disorder before generic entry. Physicians are familiar if they graduated medical school before generic entry. All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, plan type fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

Appendix A (Continued)

TABLE XXI

EFFECTS OF DRUG CLASS FAMILIARITY ON GENERIC UTILIZATION—DIFFERENTIAL EFFECTS BY NUMBER OF MOLECULES PRESCRIBED BEFORE GENERIC ENTRY

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Familiar patient	-0.0148**		-0.0017	-0.0111
	(0.0055)		(0.0060)	(0.0079)
Familiar physician (1 mol.)		-0.0357***	-0.0348***	-0.0208
		(0.0078)	(0.0083)	(0.0191)
Familiar physician (2 mol.)		-0.0280***	-0.0276***	-0.0412***
		(0.0060)	(0.0061)	(0.0074)
Familiar physician (3+ mol.)		-0.0347***	-0.0343***	-0.0302**
		(0.0080)	(0.0082)	(0.0095)
Familiar physician (1 mol.) × Familiar patient				-0.0064
				(0.0213)
Familiar physician (2 mol.) × Familiar patient				0.0429**
				(0.0131)
Familiar physician (3+ mol.) × Familiar patient				-0.00585
				(0.0152)
Adjusted R^2	0.082	0.083	0.082	0.083
Observations	36769	36769	36769	36769

Notes: Table shows the results from Equation 2.1, allowing the familiar physician effect to vary by the number of distinct molecules prescribed. Observations are at the prescription level. All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, plan type fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

Appendix A (Continued)

TABLE XXII

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—EXCLUDING REFILLS

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Panel A: Familiarity with drug class before generic entry				
Class-familiar patient	-0.0102		0.0025	-0.0123
	(0.0059)		(0.0065)	(0.008)
Class-familiar physician		-0.0306***	-0.0316***	-0.0484***
		(0.0061)	(0.0067)	(0.0087)
Class-familiar physician				0.0376**
× Class-familiar patient				(0.0122)
Adjusted R^2	0.082	0.082	0.082	0.082
Observations	32116	32116	32116	32116
Panel B: Familiarity with drug molecule before generic entry				
Molecule-familiar patient	-0.0153*		-0.0028	-0.0160
	(0.0061)		(0.0070)	(0.0083)
Molecule-familiar physician		-0.0284***	-0.0270***	-0.0504***
		(0.0065)	(0.0075)	(0.0111)
Molecule-familiar physician				0.0419**
× Molecule-familiar patient				(0.0142)
Adjusted R^2	0.082	0.082	0.081	0.082
Observations	32116	32116	32116	32116

Notes: Table shows the results from Equation 2.1. The sample excludes refills. All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, plan type fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

Appendix A (Continued)

TABLE XXIII

HIGH AND LOW MARKET SHARE STATES BY YEAR

	(1)	(2)	(2)
	Median	Low Market Share	High Market Share
2012	11.5%	Arkansas	Delaware
		Illinois	Missouri
		Pennsylvania	Oklahoma
		Tennessee	Wisconsin
		Texas	Wyoming
2013	10.5%	Arkansas	Delaware
		Illinois	Missouri
		Pennsylvania	Oklahoma
		Tennessee	Wisconsin
		Texas	Wyoming
2014	8%	Arkansas	Missouri
		Delaware	Oklahoma
		Illinois	Tennessee
		Pennsylvania	Wisconsin
		Texas	Wyoming
2015	7.5%	Arkansas	Missouri
		Delaware	Tennessee
		Illinois	Texas
		Oklahoma	Wisconsin
		Pennsylvania	Wyoming

Notes: Market share data are from Kaiser Family Foundation: https://www.kff.org/other/state-indicator/market-share-and-enrollment-of-largest-three-insurers-small-group-market. Table shows the median market share by year, and the states with below median market share ("low") and above median market share ("high).

Appendix A (Continued)

TABLE XXIV

PARAMETER ESTIMATES OF THE RANDOM COEFFICIENTS MIXED LOGIT CHOICE MODELS

	(1) No Heterogeneity	(2) Physician Heterogeneity	(3) Patient Heterogeneity	(4) Full Heterogeneity
Copayment amount	-0.0066***	-0.0054***	-0.0057***	-0.0047***
($100s)	(0.0061)	(0.0057)	(0.0018)	(0.0018)
Switching costs	0.963***	1.575***	1.853***	1.9700***
(within molecule)	(0.039)	(0.138)	(0.193)	(0.233)
Switching costs	1.097***	-0.793***	1.050***	1.278***
(across molecule)	(0.034)	(0.111)	(0.151)	(0.187)
$E_{ijt}\times$ Switching costs	-0.0023***	-0.0016***	-0.3350***	-0.2809***
(within molecule)	(0.0057)	(0.0030)	(0.0398)	(0.0504)
$E_{ijt}\times$ Switching costs	0.0030***	-0.0031***	0.0391***	0.3397***
(across molecule)	(0.0049)	(0.0027)	(0.0310)	(0.0387)
Mean α_{ikjt}	-0.0066	-0.0054	-0.0058	-0.0056
Mean $\varepsilon_{jp_{ikjt}}$	-0.0008	-0.0007	-0.0007	-0.0007
Log-likelihood	-33,764	-28,706	-27,998	-26,391
Observations	383,447	383,447	383,447	383,447

Notes: The table reports estimates of utility parameters from Equation 3.2. Column (1) does not include physician or patient heterogeneity. In Column (2), non-price drug characteristics are interacted with physician heterogeneity. Column (3) includes interactions of patient heterogeneity with price and non-price drug characteristics. Finally, Column (4) reports the full heterogeneity model shown in Table XVI. Only key coefficients are reported; demographic interactions and drug fixed effects are not reported. Own-price elasticity, $\varepsilon_{jp_{ikjt}}$, is calculated from Equation 3.4.

Appendix B

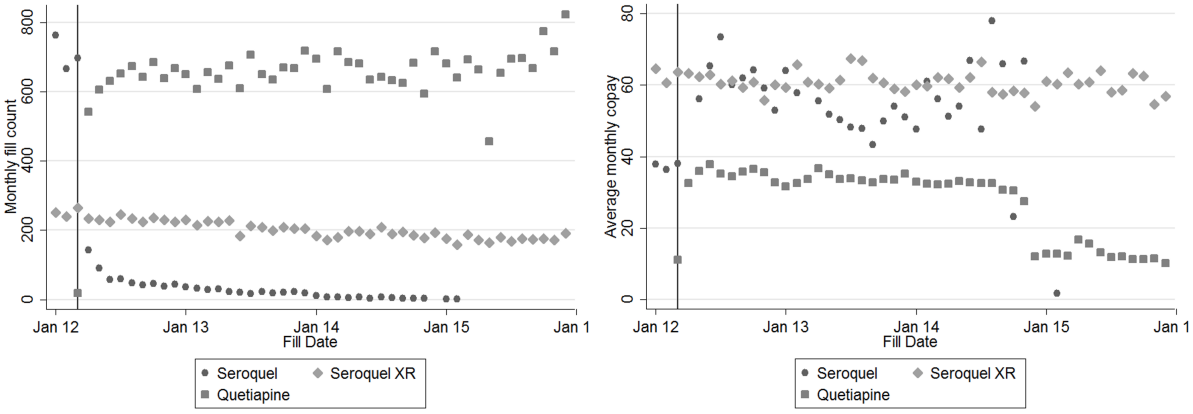
DRUG REFORMULATIONS

Drug reformulations are an important tool used by pharmaceutical firms to extend their market share in the years leading up to a patent expiry. Extended release formulations of existing brand-name drugs are a way for manufacturers facing patent expiration to grow revenue without relying on their new drug pipeline and essentially extend the life of the patent. (40) show decreases in brand utilization and increases in utilization of the reformulation up to two years prior to patent expiry, coinciding with changes in pharmaceutical marketing. Their central finding is that pharmaceutical marketing shifts demand from the cheaper generic version to the still-patented, extended release version. (41) also find evidence that manufacturers create and market reformulations to extend patent life.

AstraZeneca released Seroquel Extended Release (XR) in 2007, five years before Seroquel's patent expiration. In the main analysis, I consider Seroquel XR to be equivalent to Seroquel. The drug molecule is the same, though the extended release version has a different dosing regimen and is to be taken once-daily, as opposed to twice a day (54). Figure 13, Appendix B shows monthly utilization and copays for the molecule, separating Seroquel XR from Seroquel. For my main analysis, I do not consider the extended release version as a different product as it represent physician choice persistence toward the same brand. Physicians to whom Seroquel is promoted are also having Seroquel XR promoted to them as well. Further, there are other

Appendix B (Continued)

extended release molecules on the market at the same time—Invega (paliperidone) is extended release itself.



Prescription fills Patient spending (Copay amount)

Figure 13. Utilization and copays for quetiapine molecule

Notes: The left panel shows the total number of prescriptions written for each version of the quetiapine molecule in a month. The right panel shows the average monthly copay amount by month. The vertical line marks the month of generic entry.

In the main results (Table IV), I included Seroquel XR as a brand-name version of Seroquel. Table XXV, Appendix B shows results from the main analysis when prescriptions for Seroquel XR are dropped from the sample. For physicians and patients with drug class familiarity prior to generic entry, the effect is diminished. There is no significant effect for class-familiar patients or physicians until their interaction is included. In Column 4, class-familiar patients and physicians are both one percentage point less likely to fill a prescription for the generic

Appendix B (Continued)

drug. Physicians with drug class familiarity are one percentage point more likely to prescribe a generic drug to patients unfamiliar with the drug class than are class-unfamiliar physicians, though class-familiar physicians are about two percentage points less likely to prescribe a generic drug to patients who are also class-familiar. This is consistent with inertial prescribing behavior on behalf of concerns of medication non-adherence due to switching drugs.

In Table XXVI, Appendix B, I exclude the quetiapine molecule from the sample. Physicians with class-familiarity are 2.1 percentage points less likely to prescribe the generic version when taking into the account the interaction of patient and physician familiarity. Again, physicians prescribe differentially for familiar and unfamiliar patients—class-familiar physicians are 2.4 percentage points more likely to prescribe a generic drug to their class-unfamiliar patients, while they are 4.5 percentage points less likely to prescribe a generic to their class-familiar patients. Patients with drug molecule familiarity are 2.5 percentage points less likely to fill the generic version once it is available. Physicians familiar with the molecule are 2.3 percentage points less likely to prescribe the generic version of the molecule than molecule-unfamiliar physicians.

Drug reformulations are a valuable tool used by pharmaceutical firms to encourage continued brand drug choice despite generic availability. Reformulations are marketed aggressively, encouraging physicians to keep their patients on the brand-name, reformulated version. Releasing a reformulated drug before patent expiry creates additional demand for the brand-name product, shifting it away from the generic version.

Such extended release drug reformulations are interesting in the context of injectables for atypical antipsychotics, which have become more popular. Injectables are issued every two

Appendix B (Continued)

TABLE XXV

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—EXCLUDES SEROQUEL XR PRESCRIPTIONS FROM SAMPLE

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Panel A: Familiarity with drug class before generic entry				
Class-familiar patient	0.0050		0.0047	0.0115*
	(0.0038)		(0.0041)	(0.0049)
Class-familiar physician		0.0029	0.0009	0.0102*
		(0.0038)	(0.0041)	(0.0047)
Class-familiar physician				-0.0184*
× Class-familiar patient				(0.0076)
Adjusted R^2	0.201	0.201	0.201	0.202
Observations	30674	30674	30674	30674
Panel B: Familiarity with drug molecule before generic entry				
Molecule-familiar patient	-0.0021		0.000003	0.0024
	(0.0040)		(0.0045)	(0.0052)
Molecule-familiar physician		-0.045	-0.0045	0.0007
		(0.0043)	(0.0048)	(0.0063)
Molecule-familiar physician				-0.0083
× Molecule-familiar patient				(0.0090)
Adjusted R^2	0.201	0.201	0.201	0.201
Observations	30674	30674	30674	30674

Notes: Table shows the results from Equation 2.1. Sample excludes prescriptions for Seroquel XR. All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, plan type fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

Appendix B (Continued)

TABLE XXVI

EFFECTS OF DRUG FAMILIARITY ON GENERIC UTILIZATION—EXCLUDES PRESCRIPTIONS FOR QUETIAPINE MOLECULE FROM SAMPLE

	(1) Generic	(2) Generic	(3) Generic	(4) Generic
Panel A: Familiarity with drug class before generic entry				
Class-familiar patient	-0.0078		-0.0074	0.0137
	(0.0080)		(0.0086)	(0.0111)
Class-familiar physician		-0.0039	-0.0007	0.0240**
		(0.0080)	(0.0086)	(0.0107)
Class-familiar physician				-0.0451**
× Class-familiar patient				(0.0149)
Adjusted R^2	0.222	0.222	0.222	0.223
Observations	10523	10523	10523	10523
Panel B: Familiarity with drug molecule before generic entry				
Molecule-familiar patient	-0.0255**		-0.191*	-0.132
	(0.0081)		(0.0092)	(0.0111)
Molecule-familiar physician		-0.0227**	-0.0130	-0.0022
		(0.0083)	(0.0095)	(0.0140)
Molecule-familiar physician				-0.0164
× Molecule-familiar patient				(0.0174)
Adjusted R^2	0.223	0.223	0.223	0.223
Observations	10523	10523	10523	10523

Notes: Table shows the results from Equation 2.1. Sample excludes prescriptions for the quetiapine molecule. All regressions include a vector of physician characteristics X_i, patient characteristics Z_k, month-since-generic-entry fixed effects, month-year fixed effects, state fixed effects, plan type fixed effects, and drug molecule fixed effects. Physician characteristics are gender, practice size, an indicator for EHR use, years since medical school graduation, and specialty fixed effects. Patient characteristics include age, gender, and indicator variables for chronic condition diagnoses (diabetes, hypertension, AMI, COPD, and asthma) and mental health diagnoses (adjustment disorders, anxiety, mood disorders, personality disorders, and schizophrenia). Standard errors are in parentheses. *** indicates significance at the 0.1% level, ** at the 1% level, and * at the 5% level.

Appendix B (Continued)

to four weeks in a physician's office and so remove concerns of adherence. In the atypical antipsychotic market, several manufacturers have developed injectable versions, including Abilify Maintena, Invega Sustenna and Invega Trinza, Risperdal Consta, and Zyprexa Relprevv. Injectable reformulations are particularly interesting given the interplay between prescription drugs and office-based injectables, and are the subject of future research.

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