Incentives and Characteristics that Explain Generic Prescribing Practices

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Abstract

This study uses the National Ambulatory Medical Care Survey (2006-2010) and Health Tracking Physician Survey (2008) to study the incentives and characteristics that explain physician generic prescribing habits. The findings can be characterized into four main categories: (1) financial/economic, (2) informational, (3) patient-dependent and (4) drug idiosyncratic effects. Physicians in practices owned by HMOs or practices that had at least one managed care contract are significantly more likely to prescribe generic medicines. Furthermore, physicians who have drug industry influence are less likely to prescribe generic medicines. This study also finds consistent evidence that generic prescribing is reduced for patients with private insurance compared to self-pay patients. Drug-specific characteristics play an important role for whether a drug is prescribed as a generic or brand-name - including not only market characteristics, such as monopoly duration length, public familiarity with the generic and the quality of the generic, but also non-clinical drug characteristics, such as the length of the generic name compared the length of the brand-name. In particular, the public's familiarity with the generic has a large effect on the generic prescribing rate for a given drug. There are few differences between the generic prescribing habits of primary care physicians and specialists after controlling for the drugs prescribed.

JEL Classification: I11; I13; I18; D82; D83.

Keywords: Generic Prescribing, Physician Incentives, Patient Preferences, Principle-Agent Problem, Industry Influence, Electronic Prescribing, Drug Market Characteristics, Efficient Prescribing, National Ambulatory Medical Care Survey (NAMCS), Health Tracking Physician Survey (HTPS).

1 Introduction

In the United States, healthcare expenditure has been an area of major concern to policy makers. The growth rate in healthcare expenditure has significantly surpassed inflation and GDP growth and is expected to continue to do so in the future (Robert Wood Johnson Foundation, 2008). Thus, policy initiatives that will reduce healthcare costs while maintaining quality of care are of particular interest, especially with regards to prescription drug. As generics are significantly cheaper than their brand-name counter parts, there has been a policy push to promote generic forms to reduce medical expenditures. Thus, understanding the incentives and characteristics that affect physician generic prescribing habits is important for the formulation of policies that promote generic drug usage.

In 2010, the national healthcare expenditure totaled $2.6 trillion, 17.9 percent of GDP (Figure 1.1), of which prescription drugs account for nearly 10 percent of total expenditure (Centers for Medicare and Medicaid Services (CMS), 2012). The percentage that prescription drugs make of the total national health expenditure has steadily increased from a low of 4.7 percent in 1980 to a high of 10.4 percent in 2006 (Figure 1.2), before stabilizing and slightly declining over the last five years (CMS, 2012). Since 2003 the annual growth rate has declined significantly to only 1.6 percent (Aitken et al., 2009). Part of the slowdown can be attributed to the "primary care drug class," where there has concerted effort by insurers to promote generic drugs usage[2] and as blockbuster drugs have come of patent (Aitken et al., 2009).[3]

In 1984, the Hatch-Waxman Act (Drug Price Competition and Patent Term Restoration Act of 1984) was passed, allowing the entrance of generic drugs that could bypass expensive clinical trials if bioequivalence standards to the originator drug were met. This law has been widely considered to have created the modern generic drug industry in the United States. In 2011, 78 percent of all drugs dispensed were generics, up from just 19 percent in 1984 (U.S. Government Accountability Office (GAO), 2012). The share of drugs dispensed as generics has steadily increased since 1984, as shown in Figure 1.3 (reproduced from Berndt and Aitken (2010)), resulting in an estimated healthcare savings of $157 billion in 2010 (GAO, 2012). Generic medications represent a significant area for future cost-savings, and physician prescribing practices may influence drug dispensing practices, so it is important to understand the possible influences on physician prescribing habits.

If generics and brand-name drugs are perfect clinical substitutes, then by focusing on generic prescribing practices, the impact of the physician's decision on a patient's health does not need to be considered. The overriding question is reduced to why there may be a preference for brand-name drugs when a cheaper generic drug is available. The U.S. Food and Drug

[2]Through direct financial means such as tiered co-insurance, co-pays, deductibles for drugs. Additionally, insurers also alert physicians to the availability of generics and have given financial incentives to promote generic drug usage.

[3]This decline may reflect a slowdown in pharmaceutical innovation.

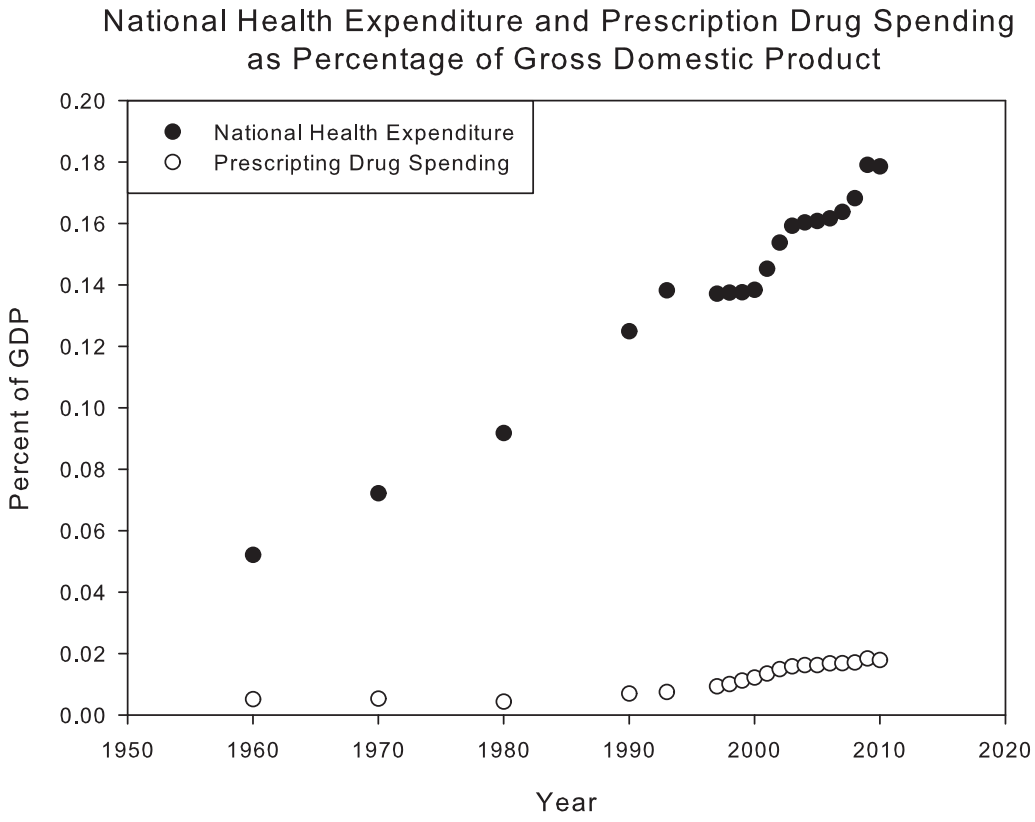

Figure 1.1: National Health Expenditure and Prescription Drug Expenditure as Percentage of GDP (CMS, 2012)

Administration (FDA) requires generics to meet strict bioequivalence standards and prove the pharmacokinetic and pharmacodynamic properties match the originator product (Williamson and Dhariwal, 2009). For many classes of drugs, studies have confirmed clinical equivalence in generic and brand-name drugs (Kesselheim et al., 2008; Moore et al., 2009; Snyman et al., 2009), although differences in the properties of generic and brand-name anti-epileptic drugs have been found (Krauss et al., 2011). Thus, for most drugs, given that a physician decides to prescribe a certain drug, the decision to prescribe the generic should be independent of unobserved medical conditions. For other medical interventions, however, this may not hold true. For example, if an oncologist were to choose between a surgical procedure and a drug regimen she would have to consider many case-specific factors in determining the most effective procedure. Because the two treatments have very different associated risks and health outcomes as well as considerations for best uses, it would be quite difficult to assess whether the physician decision making process was best for the patient or cost-beneficial. By focusing on generic drug usage, this study's findings can have broader implications for the impact of insurance-related moral hazard, the effectiveness in which the physician acts as an agent for their patients, the potential impact of conflicts of interests and the role of information on therapeutic choices on

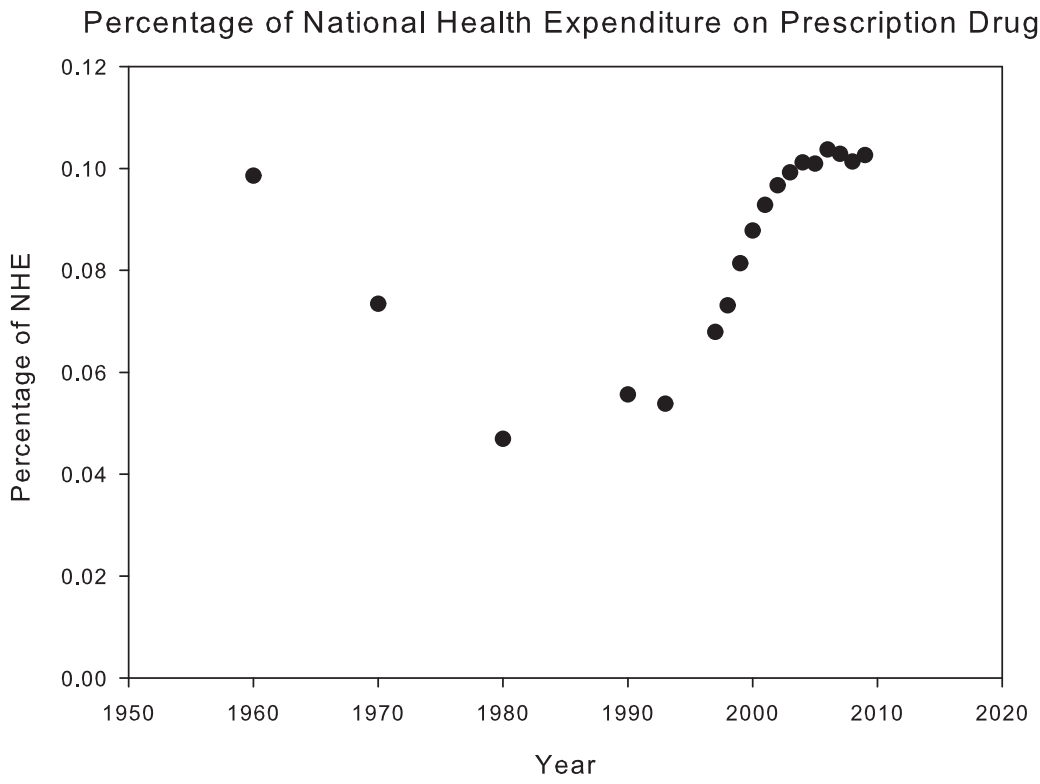

Figure 1.2: Percentage of National Health Expenditure on Prescription Drugs (CMS, 2012)

the clinical decision making process.

This study will try to address the gaps in the literature that are manifest in a few ways. First, the literature that has examined generic prescribing habits using the National Ambulatory Medical Care Survey is dated (data pre-2001) and all have placed strong emphasis on the influence of health maintenance organization (HMO) practices. Because of the recent and rapid ascent of generic medicine usage as well as the decline in popularity of HMOs, there is need for further study of physician prescribing habits. Second, not much attention has been focused on explaining drug-specific effects and the role of public's familiarity with the generic in regards generic prescribing. Studies that have examined the effect drug-specific effects have done so only on a narrow basis of a few drugs. This study analyzes a large subset of drugs to understand the variations in generic prescribing across a broad set of drugs. Also, in combination with the Health Tracking Physician Survey, the role of industry influence with regards to physician generic prescribing practices as well as the differences between self-assessed prescribing habits and actual habits can be studied.

The findings of this study can be characterized into four main categories: (1) financial/economic, (2) informational, (3) patient-dependent and (4) drug idiosyncratic effects. Physicians in practices owned by HMOs or practices that had at least one managed care contract are

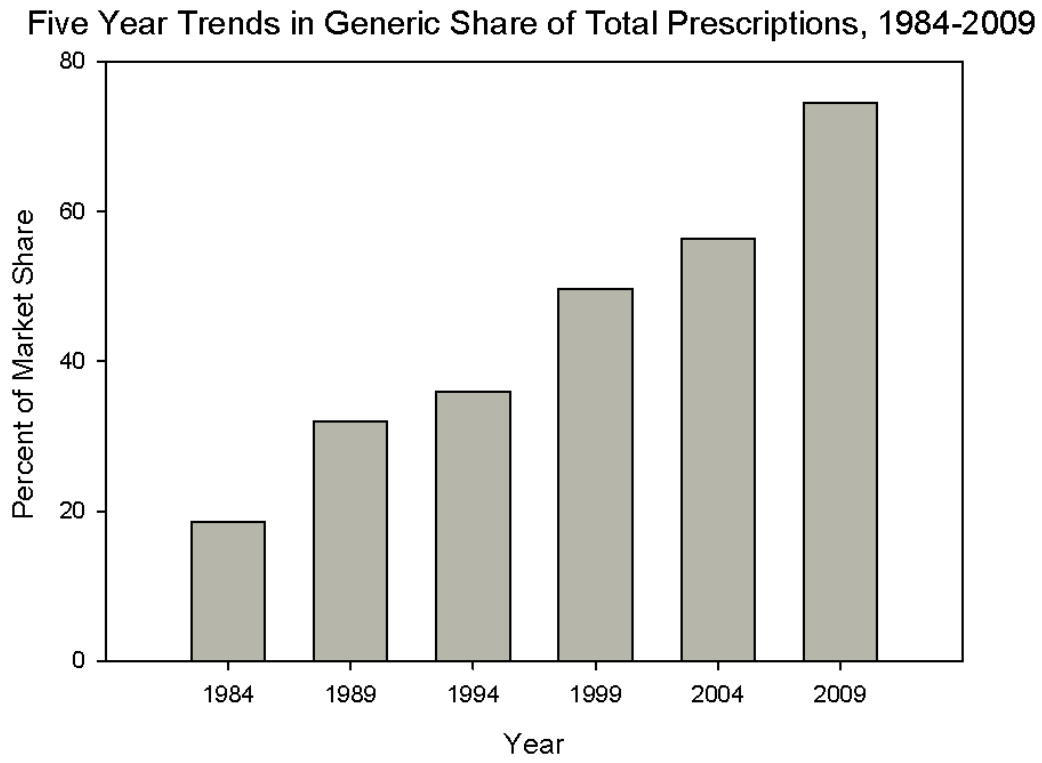

Figure 1.3: Five Year Trends in Generic Share of Total Prescriptions (Dispensed), reproduced from Berndt and Aitken (2010). Source: 1984-2004, IMS Health National Prescription Audit archives; 2005-2009, IMS Health National Sales Perspectives

significantly more likely to prescribe generic medicines. Furthermore, physicians who have drug industry influence are less likely to prescribe generic medicines. This study also finds consistent evidence that generic prescribing is reduced for patients with private insurance compared to self-pay patients. Drug-specific characteristics play an important role for whether a drug is prescribed as a generic or brand-name - including not only market characteristics, such as monopoly duration length, public familiarity with the generic and the quality of the generic, but also non-clinical drug characteristics, such as the length of the generic name compared the length of the brand-name. There is little difference between the generic prescribing habits of primary care physicians and specialists after controlling for the drugs prescribed. Characteristics that explain self-assessed generic prescribing habits are similar to those that explain actual prescribing practices.

The rest of this paper is divided as follows. Section 2 is a review of the relevant literature and prior work in this area. Section 3 describes the theoretical framework of the research. Section 4 describes the data sets used and Section 5 has relevant summary statistics. The empirical specification for this study is described in Section 6. The results and discussion are given in Sections 7 and 8, respectively. Finally, Section 9 summarizes the findings of this study.

2 Literature Review

Previous studies that have looked at physician prescribing practices have used the National Ambulatory Medical Care Survey (NAMCS) as a source for medical encounters. The seminal study on the topic of generic prescribing practices using this data set was by Hellerstein (1998), who used the 1989 NAMCS data set to examine physician prescribing behaviors. The motivation for examining physician prescribing practices was due to the seemingly small market share of generics in 1989, where only 32 percent of drugs dispensed were the generic form of the drug (Berndt and Aitken, 2010). Her findings suggested that while nearly all physicians prescribe both generic and brand-name drugs to patients, some physicians are more prone to prescribing generics while others are more prone to brand-name drugs. While some prescribing decisions could be explained by observable patient characteristics, the bulk of the evidence suggested that non-observable physician characteristics were important in the prescription decision. The empirical results, using a probit model, suggested that the patient's insurance status did not affect prescribing habits (no moral hazard issue), but practices' managed care contract status did matter. Physicians in practices that had more HMO patients were more likely to prescribe generics. This may be reflective of more price-sensitive or price-informed physicians in managed care organizations. Hellerstein found significant regional variations in generic prescribing rates - with southerners having the lowest generic prescribing rates and people in the northeast having the highest. This finding may reflect underlying regional preferences or a that information about the quality and availability of generics differs across regions (information diffusion theory) (Hellerstein, 1998; Phelps, 1992). Overall, Hellerstein suggests that as much as 30 percent of the variation in generic prescribing practices is due to unobservable physician attributes such as brand loyalty or habit persistence.[4]

Hellerstein's general methodology was replicated by Howard (1997), who looked specifically at antimicrobial drugs using the 1994 NAMCS data set. To account for price-sensitivity and brand-loyalty in generic drug usage, Howard utilized additional drug information such brand-name to generic price differentials and the time elapsed since FDA approval for each drug of interest. When including these independent variables in the model specification, Howard found strong evidence for moral hazard - with self-paying patients significantly more likely than patients with Medicare or private insurance to be prescribed generics. The author also found evidence of branding and/or habit persistence for specific antimicrobial drugs. For example, the combination drug sulfamethoxazole-trimethoprim is almost always prescribed by physicians as either Bactrim or Septra (brand-name forms), while amoxicillin is mostly prescribed as the generic. The author suggests the finding may reflect that a certain economic "branding" may have occurred and the behavior reflect the norms physicians form about a drug (i.e. the physicians refer to a drug as either the generic or brand-name). Howard finds that specialists are

[4]Berndt et al. (1995) found evidence that brand-loyalty, measured as time a drug has been on the market, was significant for determining generic market share for anti-ulcer drugs.

actually significantly more likely than non-specialists to prescribe antimicrobial drugs in their generic form, perhaps indicative that specialists are more aware of the efficacy and existence of generics, resulting in greater generic prescribing.

Rice (2011) examined the influence of HMOs on physician prescribing behavior using the NAMCS 1997-2000 data set. Her findings were similar to previous studies which found that HMO patients were more likely to receive generics and that physicians who work in HMO-owned practices are more like to prescribe generics. Rice found that physicians were sensitive to the generic-brand price ratio. She also found patient's insurance status to have an effect on the physician's generic prescribing decision, with Medicare and Medicaid patients more likely to receive generic prescriptions than those who have private insurance.

Thier (2011) used the 2008 Health Tracking Physician Survey (HTPS) to investigate the factors that affected the self-assessed generic prescribing habits, including practice and physician characteristics, information technology use, and practice revenue sources. The author found that physicians who practice in an HMO setting, who use electronic health records, were pediatricians, and those who considered patients' out of pocket costs when making care decisions were all significantly more likely to state that they always prescribe generics. In addition physicians who received compensation from pharmaceutical and device companies were less likely to always prescribe generics. By comparing generic prescription reporting between the 2008 study and an earlier 2004-2005 study, the author found that the propensity of primary care physicians to prescribe generics increased.

One of the biggest gaps in the current literature is that all of the studies have used NAMCS data sets before the widespread dispensing prevalence of generics. Even in the latest study using the NAMCS data sets, the generic dispensing rate was 42-43 percent, which was relatively constant between 1995 to 2002 (Berndt, 2002; Rice, 2011). This result, which may be due to major drugs coming off-patent within the last decade as well as greater policy emphasis to promote generic use, warrants further studies of the determinants of physician prescribing habits. The decline in popularity of HMOs suggests that there should be a reexamination of the role of HMOs in promoting generic drug usage. Furthermore, the increased prevalence of electronic prescribing has fundamentally reshaped the manner in which physicians prescribe drugs. Thus, the 2006-2010 NAMCS should be able to capture much of the modern trends in explaining generic drug prevalence.

Furthermore, the analysis is supplemented with the 2008 HTPS. While there has been analysis of the determinants of self-perceived generic prescribing habits, in order to run a logit model for the self-assessed generic prescribing habits, Thier had to dichotomized the dependent variable in the data set from a Likert scale ranging from 1 to 5 (never to always). In addition, Thier did not explore the impact of different forms of conflict of interests, such as free food, free drug samples or speaking honoraria. This study will take advantage of variances in self-assessed generic prescribing habits in the HTPS data set using a multivariate ordered logit regression

to compare physician self-reported habits with generic prescribing habits in the NAMCS data set. By using both sets of data, how physicians perceive their prescribing habits in comparison with their actual prescribing habits can be compared. Both consistencies and inconsistencies in the finding may serve as an area of focus for future researchers and policy makers.

3 Theoretical Framework

The determinants for whether a physician prescribes the generic are very complex to model and can be influenced by a host of characteristics ranging from patient characteristics, insurance characteristics, physician characteristics, drug specific characteristics, the way the physician gets information about drugs, any financial incentives the physicians may experience, regional preferences, to state laws regulating generic substitution and direct-to-physician advertising. Unfortunately, the most important determinants of prescribing are not directly observed - the physician's and patient's preferences. Instead we will have to rely on observable characteristics to glean insight onto the drivers of these preferences.

Due to the asymmetric information problem in healthcare, where the physician holds greater knowledge about diseases, diagnostics and therapies, the physician must act as the agent for the patient in medical decision making. However, the physician is also an agent of the financier of the health care (e.g. insurance company, government) and has a professional obligation to only provide medically necessary services. Thus the actions of the physicians are not necessarily based on the desires of the patient, but on the medical necessity of a therapy or intervention. Furthermore, depending on the reimbursement scheme, physicians either bear the cost or receive payment for the medical intervention. For example physicians under a capitation system bear the marginal cost of the utilization, while physicians under a fee-for-service system receive payment for the therapy and thus have a financial incentive with regards to ordering of procedures. Fortunately, because the focus of this thesis is on prescription drugs, which are not dispensed by physicians,[5] direct financial incentives should not have a large impact on prescribing practice.[6]

3.1 Modeling the Decision to Prescribe a Generic

The patient's preference for a prescription of a generic or brand-name form of a drug is principally determined by the quality and cost differences between the generic and brand. Hence, assuming the generic has a cost, C_G, which is less than the cost of the brand-name, C_B, the patient would choose to have the brand-name prescribed only if the brand-name form had a higher quality value, Q_B, over the quality value of the generic, Q_G, such that $Q_B - Q_G > C_B - C_G$.

If the patient has insurance, the patient may not perceive a difference in the cost of the

[5]Drugs that the physician would dispense, such as vaccines, are excluded from the analysis.

[6]Liu et al. (2009) found that financial incentives had significant impacts on generic prescribing habits in Taiwan (where physician dispense medicines).

generic and brand-name form of the drug or perceive a reduced price differential if their insurance has tiered a co-pay or small deductable (moral hazard). Hence, patients with insurance will be more likely to be prescribed the brand-name form of the drug if the brand-name form is of even marginally perceived to be of higher quality. Similarly, we would expect that patients without insurance (i.e. self-pay) would be more price-sensitive and receive the generic at higher rates.

Furthermore, *a priori*, physicians and patients do not know the quality of the generic relative to the brand-name form of the drug. Thus, there is a cost to ascertain the quality of the generic and a rational consumer would choose to have the generic form of the drug prescribed if $Q_G - Q_B > C_B - C_G + C_I$. This information cost, C_I, can also be considered a switching cost and means that a price differential between the brand-name form and generic form (of equivalent quality) can persist for a given drug. This switching cost is a function time. Empirically, this means that generic prescribing practices should change over time, after the generic is introduced, as physicians become more familiar with both the existence and quality of the generic.[7] If the patient gets utility from buying the brand-name version of the drug then essentially the patient has a willingness to pay premium, Q_{Taste}, for the brand-name form. Under perfect agency, physician characteristics should not influence generic prescribing habits.

Generic substitution laws allow for the patient (or pharmacist) to substitute the prescription, when the drug is dispensed. That is, the decision to purchase the brand-name or generic form of the prescription is determined when the drug is dispensed and not necessarily when the prescription is written. Every state allows for the substitution of the generic form if the physician prescribed the brand-name (Vivian, 2008).[8] In some states the generic substitution laws mandate that the generic form of the drug is dispensed unless otherwise stated by the physician, while other states merely allow for the substitution of a generic for a prescription written for the brand-name. This substitution can occur without the consent of the patient. The effect of these laws may in fact result in the physician writing the prescription for the brand-name form of the drug in order to ensure that patients are given the choice to exercise their preference for the brand-name or generic form of the drug. The effect of generic substitution laws are essentially to de-link the physician's prescription from what is dispensed and we can expect to see lower generic prescribing rates compared with the actual dispensing rates of generic drugs. Unfortunately this also means that without a data set that links the prescribing habits of physicians to the drugs dispensed it is difficult if not impossible to quantify the impact that physician prescribing habits would incur on healthcare costs.

[7] Please see Hellstrom and Rudholm (2010) "Uncertainty in the generic versus brand name prescription decision," for a comprehensive theoretical modeling of the switching costs for physician generic prescribing.

[8] Substitution is not allowed if the physician indicates that the brand is necessary.

3.2 Expected Findings

First, patients are one of the major driving influences of whether the generic is prescribed (as they can request a specific prescription from their physician). From the literature, we would expect certain patient characteristics, such as insurance type, may impact the physician's prescribing habits. Specifically, with regards to insurance type, we would expect that patients with insurance be more likely to receive the brand-name form of the drug as they are less sensitive to the price of the medication.

Similarly, the physician's characteristics will be strongly related to generic prescribing habits. There have been contradictory findings in the literature about the generic prescribing habits of primary care physicians and specialists. Primary care physicians may be more likely to prescribe generics as the recent leveling in drug expenditures has been due to the increase in generic usage in the "primary care" drug class (Aitken et al., 2009), however, when controlling for the type of drugs prescribed specialists were more likely to prescribe generics, perhaps because they were more informed of the existence and accepting of the efficacy of the generic (Howard, 1997). Thus, this study aims to reconcile whether there are differences in generic prescribing habits among primary care physicians and specialists in general, as well as when controlling for the type of drug prescribed. Other practice characteristics, such as ownership status, may also be important. Physicians that are HMO owned may have strong incentives to prescribe generics, and have previously been shown to have higher generic prescribing rates (Hellerstein, 1998; Rice, 2011).

Physicians will likely be strongly affected by a variety of drug specific characteristics. This can range from the length of time the originator drug was exclusively on the market, the length of time that generics have been available, whether the drug is classified as part of a narrow therapeutic index, the drug class, the effort it takes to write the brand-name or generic name, and drug idiosyncratic characteristics. Generally speaking, we would expect that the longer the originator drug had market exclusivity, the lower the generic prescribing rate would be for that drug. On the other hand the longer a generic competitor has been on the market, there would be a higher generic prescribing rate. Drugs classified as having a narrow therapeutic index (NTI)[9] would probably be prescribed in the generic form less often as the physician may be more wary of the quality of the generic.[10]

Lastly, as significant idiosyncrasies in drug characteristics may exist, the regression model needs to have a rich specification on drug characteristics in order to limit confounding effects on the overall generic prescribing rate. For example, there are significant differences between the

[9] NTI drugs are those that have a narrow therapeutic range for which they are clinically effective, but not toxic to the patient. For example warfarin/Coumadin, an NTI drug, is an anti-coagulant can be dangerous outside of a narrow range of blood concentration.

[10] It is not that generic forms of NTI drugs are less likely to be bioequivalent, but due to the dangers involved with NTI drugs physicians may be more risk-averse in deviating from the brand-name (which they are more familiar with).

generic prescribing rates between drugs such as amoxicillin (an antibiotic, which is generally prescribed as the generic form) and acetaminophen-hydrocodone (a combination narcotic pain medicine, which is generally prescribed as the brand-name Vicodin). Furthermore, certain drug classes may be more prone to generic prescribing than others (perhaps related to the perception of whether generics drugs of a particular class are more therapeutically equivalent). Rice found that calcium channel blockers were less likely to be prescribed as a generic, while beta blockers, ace inhibitors, and anti-depressants were all more likely to be given as generic.[11] A specification that does not control for drug-specific effects it could certainly bias patient and physician characteristics which explain generic prescribing habits. Additionally, this study will look at the role of public familiarity with the generic drug on generic prescribing habits, where greater public familiarity with the generic should result in greater generic prescribing of the drug if patients have an influence on physician.[12]

4 Data

This study examines two distinct data sets: the National Ambulatory Medical Care Survey (NAMCS), 2006-2010,[13] and the Health Tracking Physician Survey (HTPS), 2008.[14] In addition, drug-specific market characteristics are incorporated to create a richer set of covariates, such as drug exclusivity information (to control for habituation and branding effects), whether a drug is considered as part of a narrow therapeutic index and the effect public familiarity with the generic. The data sets and variable creation are described in detail in the following sections.

4.1 National Ambulatory Medical Care Survey (2006-2010)

The National Ambulatory Medical Care Survey (NAMCS) is a nationally representative survey of physicians with multiple patient patient-encounters per physician. The analysis is limited to the 2006-2010 pooled, cross-sectional data set as they are the most recent and most similar to each other (in terms of survey variables). This data set allows for specific analysis of generic prescribing habits by looking at the medication prescribed during each encounter.

[11] Unfortunately, the National Ambulatory Medical Care Survey changed the drug classification system, so making a direct comparison with Rice's findings is not possible.

[12] Campbell et al. (2013) found in a recent survey that physicians acquiesce to patient demands, with 4 out of 10 physicians indicating that they sometimes or often prescribe a brand-name to a patient when a generic is available because the patient requested it. Physicians who practiced for more than 30 years were more likely to acquiesce than physicians in practice for 10 years or less, and pediatricians, anesthesiologists, cardiologists, and general surgeons were significantly less likely to acquiesce to patient demands relative to internal medicine physicians. Physicians who had more industry relationships, such as receiving free food or beverages, receiving drug samples, or meeting often with industry representatives, were also more likely to prescribe the brand-name if patients demanded it.

[13] The NAMCS data set is published by the National Center for Health Statistics and was downloaded from the Interuniversity Consortium for Political and Social Research (ICPSR).

[14] The HTPS data set is published by the Center for Studying Health System Change and was downloaded from the ICPSR.

The NAMCS has practice characteristics, physician characteristics, patient characteristics, but does not have information about interactions with pharmaceutical sales representatives or other forms of industry influence.

Because the NAMCS questionnaire and coding of variables have changed between the years 2006 and 2010 considerable efforts are made to ensure that the variables were encoded properly and consistently. Unfortunately, because the NAMCS has either redefined certain measurements in its questionnaires or what is publically accessible over this period, it is necessary to recode certain variables like race and visit history. In general, all regressions are estimated with included variables that preserve the granularity of the data, without dropping observations. Observations in which the physician did not respond to an included survey question are dropped from the analysis.[15]

The NAMCS data set includes both the name of the drug prescribed[16] as well as the generic name of the drug.[17] To create a measure of whether the drug prescribed was the generic or brand-name form, a comparison is made between the name of the drug written as the prescription and the generic form of the drug. If the prescribed drug name matches the generic name of the drug, then the encounter is encoded as a generic prescription. If the drug name does not match then the encounter is coded as a brand-name prescription. Because the NAMCS is not entirely consistent between the names used for the drug coding of the two variables an exact name-match methodology is not sufficient.[18] In order to properly code encounters, the matching is done on a word-by-word basis instead of the entire entry. This method has a tendency to incorrectly label some prescriptions as generics, as some brand-names partially have the same name as the generic name. Every effort was made to find and manually correct these improperly classified encounters.

In order to get a consistent and meaningful analysis, this study is constrained by the completeness of the description for the "generic" and "brand-name" names of the drugs provided by the NAMCS database. Unfortunately, biologics and supplements are generally only coded by the generic name of the product (e.g. "Hepatitis Vaccine", "Vitamin A", "Iron Supplements"), without consideration of the trade names of the product prescribed. For this reason, all prescriptions for these types of products are excluded from the regression results.[19] Furthermore, since this analysis is based on the physician's choice to prescribe the generic, only

[15]Excluding observations where the physician did not respond to an included survey question may introduce some bias in the regression estimate. However, there is evidence of systematic differences in physician characteristics between included and excluded observations.

[16]Drug prescribed is determined by MED1 variable.

[17]Generic name is determined by DRUGID1 variable.

[18]The MED1 variable (physician's response to questionnaire) often times includes additional information about the drug prescribed (e.g. whether it is an extended release formulation or the base/salt conjugate the drug is in). For example the drug "metformin" (DRUGID1) can be encoded by the physician as "metformin hydrochloride ER" (MED1) and "codeine-guaifenesin" (DRUGID1) as "guaifenesin w/ codeine" (MED1).While both were prescribed as the generic, an exact name-matching algorithm would have coded them as a brand-name prescription.

[19]Vaccines would be excluded regardless, as they are often dispensed by the physician.

drugs that are multi-source are of interest. Due to the size of the data set, it is infeasible to manually determine whether a drug has a bioequivalent substitute on the market. Thus the determination of multi-source is based on whether in the entire data set there are at least two different prescriptions for a given chemical entity (i.e. that the generic prescribing rate for a drug is between 0 and 1 non-inclusively).[20] This study also looked at the generic prescribing habits for the top forty drugs in the sample with additional data on market characteristics of the drugs (discussed below). For these drugs, multi-source refers to only drugs with a generic on the market.

4.2 Supplementary Drug Data

It is necessary to include data from the FDA Orange to address the possible confounding effects of drug specific characteristics such as monopoly duration length. The FDA provides a list of approved generic competitors and date of approval of the originator and generic competitors (if after January 1, 1982) in the publically available Orange Book. The Orange Book also contains information about whether there are any clinical equivalence concerns with the generic. As it is infeasible to collect this data for every drug , the data is gathered for the top forty drugs in data set. Among the subsample of drugs analyzed, the top forty drugs prescribed, there are no variations in therapeutic equivalence codes. Two drugs were considered as part of a narrow therapeutic index, for which, in a few states, pharmacists cannot substitute for the generic form of the drug. Unlike previous studies, drug price differentials are not included as variations drug prices are likely endogenous to the popularity of the generic.

Data from Google search trends were included as a proxy for the public's familiarity with the generic form of the drug. The Google search trends database, gives a measure of the relative number of weekly searches for the generic name or brand-name, for a drug of interest, over the 2006-2010 period for the United States. In order to reduce noise in the data set, the number of searches for the generic and brand-name were averaged and calculated by quarter (i.e. Q1 2006). The relative generic share of the searches is calculated as the number of generic searches divided by the sum of generic and brand-name searches, as follows.

$$\text{Generic's Search Popularity}_t = \frac{\text{Generic Searches}_t}{\text{Generic Searches}_t + \text{Brand-Name Searches}_t}$$

[20] This measure of multi-source is not exact. A patented drug might not have a competitor on the market even if a physician prescribes the generic name for the drug (method incorrectly labels the drug as multi-source). Conversely, even if there are competitors are on the market, if the physicians in the sample never prescribe it as the generic or brand-name then it will be incorrectly considered single-source. However, this methodology is a reasonable approximation of the determination of a multi-source drug as it is infeasible to systematically determine whether the thousands of drugs in the full sample have competitors as it captures the subset of drugs that physicians have shown a "choice" in their prescription.

4.3 Health Tracking Physician Survey (2008)

The 2008 Health Tracking Physician Survey (HTPS) is a nationally representative mail survey of U.S. physicians providing at least 20 hours per week of direct patient care.[21] While the physician's perception of generic drug prescribing habits are asked in the 2004-2005 survey, the 2008 survey asks physicians about their relationship with pharmaceutical industry sales representatives; asking if they have received free food, drugs, trips, speaking engagements, etc. The rest of the variables in this data set are about the practice and physician characteristics. This data set is limited in usefulness as it does not contain patient-encounter specific information such as patient and drug characteristics.

The HTPS asks physicians about their generic prescribing habits when a generic is available on a 1-5 Likert-scale (1 = Never, 5 = Always).[22] This measure is limited as it is self-assessed and ranked on a subjective scale (what a rating means may be different for different physicians). However, general trends in the data should still be evident. In order to get a measure of the incentives that motivate prescribing practices, a multivariate ordered logit regression is run to show the effects of covariates of interest on the odds of incrementally moving from one rating to the next (e.g. from a 4 to a 5). While it is unlikely the odds of incrementally moving from a 1 to a 2 is the same as moving from a 4 to a 5, the ordered logit model will estimate the average effect.

5 Summary Statistics

5.1 NAMCS Summary Statistics

An analysis of the drugs prescribed is completed in order to get a deeper understanding of market and drug-specific effects. Table 5.1 shows the popularity of the drugs that are prescribed in the NAMCS data set organized by either the branded name or the generic name of drug from the first prescription encoded for each patient.[23] The number of times a drug is prescribed varies significantly. While, 1,388 unique drugs are recorded, the top forty drugs by active ingredient represent 40 percent of all drugs prescribed. Thus, an analysis that is limited to only the top drugs in the data set is still quite representative of prescribing habits.[24]

There is a great deal of variation in the generic prescribing rates by drug, with some drugs that are overwhelmingly prescribed in either the generic or brand-name form. Figure 5.1 (top)

[21] The sample of physicians was drawn from the American Medical Association master file, excluding residents and fellows, as well as radiologists, anesthesiologists and pathologists.

[22] The survey asked: "If a generic option is available, how often do you prescribe a generic over a brand name drug?"

[23] Please refer to the NAMCS Appendix for an explanation of why this methodology can be done even though the generic prescribing rates for the first drug mention differs from the second, third, fourth, etc. drug mentions.

[24] However, the results from this analysis may not be globally applicable to the less popular drugs as these drugs are likely to be significantly different in terms of drug class, market characteristics, and physician and patient familiarity with the drug.

Table 5.1: Summary Statistics for Drugs Prescribed, 2006-2010

Measure	Statistic
By Brand Name	
Number of Unique Drugs	2817
Number of Prescriptions	87,573
Number of Prescriptions, Top 40 Drug	26,985
Percentage, Top 40 Drug	30.8%
Percentage of Drugs with 10+ Prescriptions	94.0%
Percentage of Drug with 100+ Prescriptions	67.2%
Number of Prescriptions, 10th Percentile	18
Number of Prescriptions, 25th Percentile	67
Number of Prescriptions, 50th Percentile	211
Number of Prescriptions, 75th Percentile	500
Number of Prescriptions, 90th Percentile	830
By Generic Name	
Number of Unique Drugs	1388
Number of Prescriptions	87,342
Number of Prescriptions, Top 40 Drug	34,956
Percentage, Top 40 Drug	40.0%
Percentage of Drug with 10+ Prescriptions	97.5%
Percentage of Drug with 100+ Prescriptions	80.1%
Number of Prescriptions, 10th Percentile	44
Number of Prescriptions, 25th Percentile	131
Number of Prescriptions, 50th Percentile	348
Number of Prescriptions, 75th Percentile	825
Number of Prescriptions, 90th Percentile	1471

shows a histogram of the distribution of mean generic prescribing rate for (left) all the drugs in the sample and (right) drugs with at least 500 mentions. There is a clear bimodal distribution of generic prescribing rate, where drugs are either highly likely to be prescribed as a generic or highly likely to be prescribed as a brand-name. This finding could be a reflection of a combination of habituation and peer effects (Howard, 1997).[25]

Generic prescribing of drugs could also be significantly affected by physician preference. To measure the variations in physician prescribing habits, the mean generic prescribing share for all physicians in the data set is calculated using the first prescription for all patients that a physician saw. There is a great deal of variation in generic prescribing rates, with the distribution looking roughly normal, except for spikes showing a large number of physicians who made no generic prescriptions and those who made only generic prescriptions (Figure 5.1, bottom). These spikes could be because some physicians only prescribed a few drugs or due to specialization, the physician only prescribed a certain drug or class of drugs (that may be generally prescribed

[25] A drug could be generally prescribed as either the generic or brand-name based on the norms developed by physicians over time.

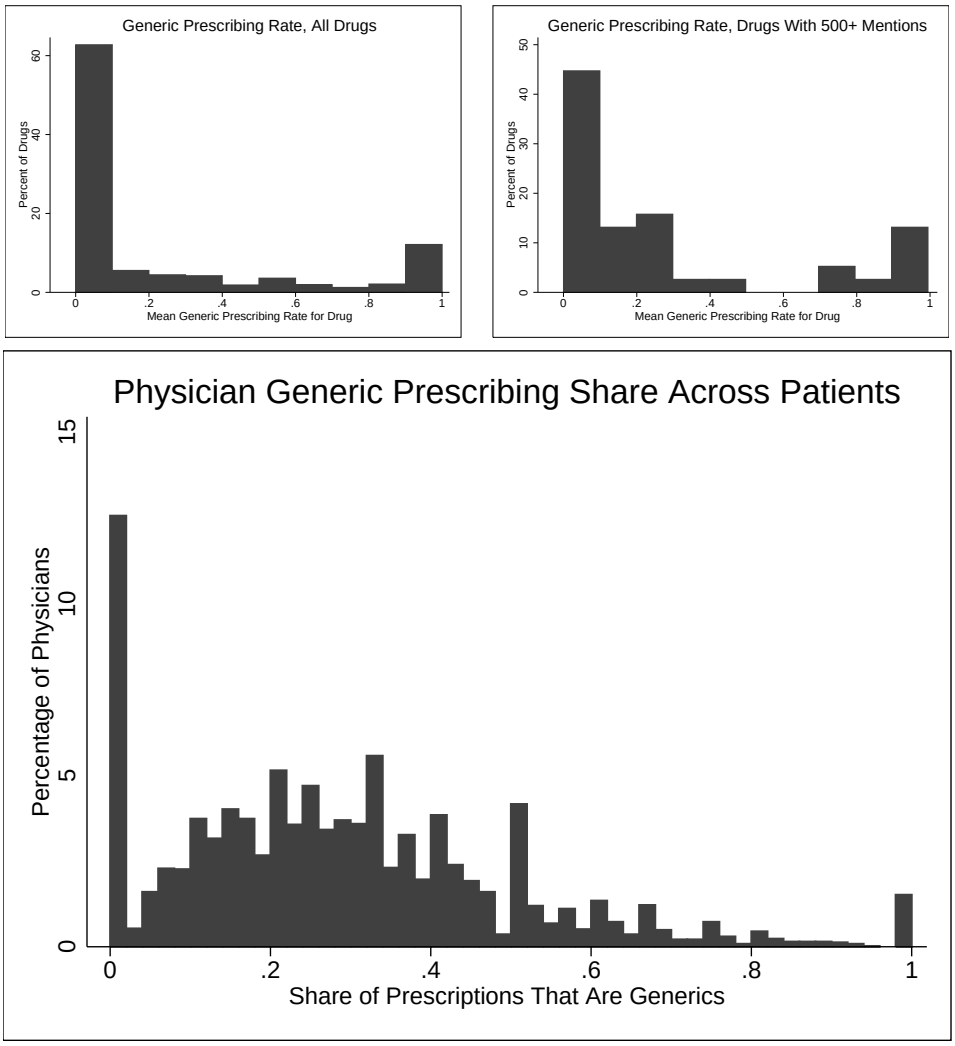

Figure 5.1: (Top) Drug-Specific Generic Prescribing Distribution by Number of Prescriptions: (Left) All the Drugs and (Right) Drugs with 500+ Prescriptions; (Bottom) Physician Generic Prescribing Distribution

in either the generic or brand-name form), and thus reflects drug-specific generic prescribing characteristics rather than a characteristic of the physician. The findings overall, however, suggest that we can utilize the variation in generic prescribing share to estimate observable physician-specific prescribing habits.

Among the entire sample, the average generic prescribing rate is around 31.2 percent, which is significantly lower than the share of drugs dispensed as a generic.[26] The generic prescribing rate varies quite significantly with the survey year over this time period - starting at a generic prescribing rate of 24.5 percent in 2006, and increasing dramatically to 39.3 percent in 2010.

[26] As we would expect, due to the effect of generic substitution laws allowing for the substitution of the generic form for the branded drug.

This trend is perhaps reflective of drugs coming off patent or increasing pressure to prescribe generic medicines to reduce healthcare costs. In addition, there are significant differences in generic prescribing rates by physician characteristics. The mean statistics and generic prescribing rates (GPR) of relevant variables of interest that are used in the analysis are listed in Table A.6 (NAMCS Appendix).

5.2 HTPS Summary Statistics

The distribution of physician ratings for their generic prescribing habits shows how physicians assessed their own prescribing habits. There are very few ratings of never (1) or rarely (2) in the data, with the vast majority of ratings came in the sometimes (3) to always (5) range (Figure 5.2). The average rating is a 4.11 ($\sigma = 0.76$).[27]

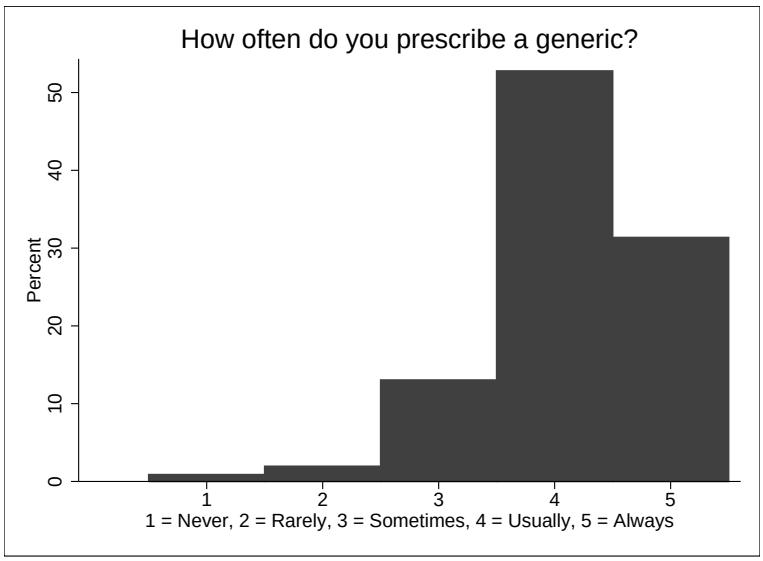

Figure 5.2: Physician Self-Assessed Generic Prescribing Habits

Additionally, the importance of the HTPS data set is that it surveyed physicians on industry influences. The survey asked whether the physician received free food, free drug supplies, honoraria for speaking, honoraria for prescribing practice surveys, payment for consulting services, paid for the cost of travel to attend meetings, complementary or subsidized admissions to conferences awarding continuing medical education (CME) credit, any other gifts,and the total compensation from drug, device and other medically-related companies.[28] There is a great deal of variation in the prevalence of the different industry influences variables with free food and free drug samples being widely prevalent (73 to 75 percent of all physicians) but paid speaking,

[27]Social desirability bias may result in physicians overstating their generic prescribing habits.

[28]The corresponding variables in the data set are FREEFD, FREERX, HNSPEAK, HNSRVY, PYCNSLT, CSTTRVL, CMECRDT, GFTOTHX and MRELCMPX. Note that all variables are dummies except for the total compensation which is categorical (0-4) for payments received ranging from $0 to over $5,000.

Table 5.2: Summary Statistics of Industry Influence Variables

Variable	Mean of Survey
Free food or beverages (workplace)	0.7333
	(0.0066)
Free drugs samples	0.7467
	(0.0065)
Speaking honoraria	0.1558
	(0.0054)
Prescribing survey honoraria	0.2977
	(0.0068)
Payment for consulting	0.1096
	(0.0047)
Travel costs for meetings	0.1058
	(0.0046)
Paid CME conference admission	0.1361
	(0.0051)
Received other gifts	0.0561
	(0.0034)
Number of industry influences (max 8)	2.3413
	(0.0227)
At least one industry influence	0.8818
	(0.0048)
Number of industry influences (max 6)	0.8602
(excluding free food and drugs)	(0.0171)
At least one industry influence	0.4952
(excluding free food and drugs)	(0.0074)

NOTE – Standard errors in parentheses.

travel and consulting being far less common (5 to 22 percent), as described in Table 5.2. Half of the physicians in the sample admitted to at least one industry influence, excluding free food or free drugs.[29]

6 Empirical Specification

6.1 NAMCS Empirical Specification

For the NAMCS, as the decision to prescribe a generic is binary, the main models that will be used are ordinary least squares (OLS) (due to large sample size) and logit regressions on generic prescribing habits for the pooled, cross-sectional data set, as follows:

$$\hat{G}_{ijdt} = \alpha_j + \gamma_t + \beta_X X_i + \beta_I I_i + \beta_P P_j + \beta_D D_d + \epsilon_{ijdt} \tag{6.1}$$

The decision on whether or not to prescribe the generic version of the drug ($\hat{G}_{ijdt}$), for the

[29]Free drugs can considered an "experience good."

dth drug, ith patient and jth physician, is dependent on α_j, the geographical fixed effects; γ_t, the time fixed effects; X_i, a vector of patient characteristics; I_i, a vector of insurance characteristics; P_j, a vector of physician and practice characteristics; and D_d, a vector of drug characteristics. Variables that are included are described in further detail in Table 6.1.

Table 6.1: Model Specification (Similar for Both NAMCS and HTPS)

Variable	**Description**
G_{ijdt}	1 if generic is prescribed, 0 if brand-name is prescribed. This is determined by comparing the name of the medicine that the physician prescribed with the generic name (active ingredient) of the drug.
α_j	Regional fixed effects based on physician practice location.
γ_t	Time fixed effects.
X_i	Patient characteristics (e.g. age, sex, race, ethnicity, reason for visit, visits history, new or continued medicine, etc).
I_i	Patient's payment source.
P_j	Physician and practice characteristics (e.g. primary care, specialty, ownership status, affiliations, etc).
D_d	Drug characteristics. Controls for the major drug classes or controls for each drug in the data set. Drug characteristics: combination drug, controlled substance and whether the generic name is shorter than the brand-name. For the top forty drugs in the data set: monopoly duration period, approval pre-1982, NTI drug classification, has an extended release formulation and the public's familiarity with the generic name.

It is also necessary to estimate a two-stage least squares (2SLS) regression as it can be expected that the measure of public familiarity with the generic name (approximated by the relative popularity of generic searches to brand-name searches on Google) of a drug could have reverse causation with physician prescribing (i.e. the Google searches are in response to prescriptions written by physicians). To control for this, the covariate is instrumented on the monopoly duration length and whether the drug was approved before 1982. Both of these variables are shown to have little significance after controlling for the public's familiarity with the generic. The specification is as follows.

$$\hat{G}_{ijdt} = \alpha_j + \gamma_t + \beta_X X_i + \beta_I I_i + \beta_P P_j + \beta_D D_d + \beta_S \hat{S}_{dt} + \epsilon_{1ijdt} \tag{6.2}$$

$$\hat{S}_{dt} = \alpha_j + \gamma_t + \beta_X X_i + \beta_I I_i + \beta_P P_j + \beta_D D_d + \beta_M \text{Mon Dur}_d + \beta_{1982} 1982_d + \epsilon_{2ijdt} \tag{6.3}$$

Where the public's familiarity with the generic, S_{dt}, is estimated in the first stage of the regression as $\hat{S}_{dt}$, and used as an independent variable in the second stage of the regression.

6.2 HTPS Empirical Specification

A limitation of using the HTPS data set is not only that it is a self-assessed measure, but also that there is no clear definition of what a rating translates to in terms of real prescribing habits. However, it likely that this self-assessed measure can still be indicative for the characteristics

that motivate physician prescribing habits. As the dependent variable is ordinal and non-continuous, in the physician's generic prescribing habits are estimated using a multivariate ordered logit regression. The ordered logit model (proportional odds model) is an extension of the dichotomous logit model, with the assumption that the effect of the independent variable is the same between categories. Thus, the empirical specification of the HTPS model is as follows:

$$G_i^* = \alpha_i + \beta_I I_i + \beta_P P_i + \beta_C C_i + \epsilon_i \tag{6.4}$$

$$G = \begin{cases} 1 & \text{if } G^* \leq \mu_1, \\ 2 & \text{if } \mu_1 \leq G^* \leq= \mu_2, \\ 3 & \text{if } \mu_2 \leq G^* \leq= \mu_3, \\ 4 & \text{if } \mu_3 \leq G^* \leq \mu_4, \\ 5 & \text{if } \mu_4 < G^*. \end{cases}$$

Where, G_i^* , the continuous latent variable for the ith physician's self-assessed measure of prescribing generics, is dependent on α_i, the geographical fixed effects; I_i, a vector of practice revenue characteristics; P_i, a vector of physician and practice characteristics; and C_i, a vector of conflict of interest measures. The cutoff μ_k, for the kth ordinal category, determines the categorization of the continuous latent variable G_i^* to the predicted ordinal dependent variable, G_i. The observed odds-ratio to be in a higher category can be calculated, for the kth ordered category, as follows.

$$\frac{\Pr(\mathrm{G}_i > k)}{\Pr(\mathrm{G}_i \leq k)} = \exp(\mu_k + \alpha_i + \beta_I I_i + \beta_P P_i + \beta_C C_i)$$

7 Results

7.1 NAMCS Baseline Analysis

To analyze some of the possible determinants of physician generic prescribing behavior, an OLS regression with clusters based on physician is estimated.[30] Due to the large sample size (N = 61,295) and number of variables (54 to 468) included in the regression, a logit model was inefficient in calculating the marginal effects. However, the marginal effects of the variables from the logit model did not appreciatively differ in comparison to the OLS specification. Three models were estimated and are shown in Table 7.1.

[30]Standard errors based on physician cluster uses physicians as the unit of observation rather than patient encounter to minimize the effect of multiple observations per physician (Rice, 2011). In comparison to non-clustered robust standard errors, the clustered standard errors tended to be larger, reducing the statistical significance of most covariates.

The first model is the primary specification with time and regional effects, drug class dummies, drug characteristics dummies (whether drug is combination therapy, controlled substance, and whether the generic name is longer than the brand-name), patient characteristics, patient payment source, and practice characteristics. The second model also includes controls for physician specialties (estimates not shown). While some specialties, such as OBGYN, dermatology, urology, and psychiatry had lower generic prescribing rates compared to general/family practitioners ($p < 0.001$), the magnitude of the effects were only moderate in size (largest is 0.067). Once drug controls were included in the specification (model not shown), most of the effects were statistically insignificant except for urology and orthopedic surgery at the 5 percent level. This finding suggests that the physician specialty dummies are capturing part of the drug-specific effects that the drug class dummies are not capturing. The third model is an over-specified OLS with controls for each drug in the sample. The utility of this regression is to test if the coefficients of the first and second model are still statistically significant and not driven by differences in the drug case-mix.

The estimates suggest that there is a strong effect on generic prescribing habits due to region, with the South having slightly lower generic prescribing rates (3.2 percentage points) and the West having slightly higher generic prescribing rates (4.3 percent points) in comparison with the Northeast. Such a finding, suggests differences in information diffusion rates across regions with respect to quality and availability of generics (Phelps, 1992) and generally matches earlier literature Hellerstein (1998) (NAMCS 1989) and Rice (2011) (NAMCS 1997-2000), except that there has been a trend towards reduced differences in generic prescribing rate by region. Perhaps as there have been fewer novel drugs brought to market in the last decade, the differences in generic prescribing rates have subsided, consistent with the information diffusion theory.

A number of covariates suggest that physicians and patients are somewhat sensitive to the price differential between the generic and brand-name and that this tends to increase the generic prescribing rate. Physicians who practice in HMO-owned practices (2 percent of practices) prescribe generics at much higher rates relative to their peers, at a 22.3 percent higher level. Similarly, physicians in practices that had no managed care contracts (80 percent of practices) prescribed generics at a 2.3 percent lower level. Physicians who practice in zip codes with poverty levels of 5 percent or greater prescribe generics at 1.6-1.8 percent higher level. Patients also showed signs of price sensitivity, with patients who had private insurance, Medicare, Medicaid, and workers' compensation, all receiving generic prescriptions at a lower rate compared to patients who self-paid (5.25 percent of sample). The magnitude of the effect of insurance status, however, is rather small, with patients with private insurance having only a 2.7 percent lower level in generic prescribing ($p < 0.001$). This effect cannot be entirely attributed to drug case-mix,[31] as the third OLS specification, which includes dummies for each drug in the sample, still finds that patients with private insurance have a 1 percent lower level in generic

[31] That patients who were self-insured receive a different set of drugs compared to self-pay patients.

Table 7.1: OLS Regression for Determinants of Generic Prescribing Behavior

Variable	(1)		(2)		(3)	
	β	**SE**	β	**SE**	β	**SE**
Fixed Effects						
Midwest	0.0150	0.0088	0.0137	0.0089	0.0027	0.0074
South	-0.0323***	0.0082	-0.0325***	0.0082	-0.0233**	0.0068
West	0.0425***	0.0093	0.0413***	0.0093	0.0346***	0.0076
MSA	-0.0047	0.0083	-0.0054	0.0083	-0.0004	0.0073
Poverty 5-9.99%	0.0184**	0.0059	0.0185**	0.0059	0.0107*	0.0048
Poverty 10-19.99%	0.0160*	0.0063	0.0167**	0.0063	0.0041	0.0052
Poverty 20%+	0.0185*	0.0076	0.0188*	0.0076	0.0052	0.0063
Drug Characteristics						
Combination	-0.2228***	0.0068	-0.2225***	0.0070	-0.0392	0.0253
Not Controlled Substance	0.0014	0.0104	0.0010	0.0105	-0.0200*	0.0091
Generic Name Longer	-0.4752***	0.0077	-0.4728***	0.0078		
Patient Characteristics						
Age	-0.0005***	0.0001	-0.0004**	0.0001	0.0003**	0.0001
Male	0.0102**	0.0038	0.0097*	0.0040	0.0073*	0.0031
Hispanic	0.0288***	0.0072	0.0276***	0.0072	0.0163**	0.0060
Black	0.0155*	0.0067	0.0169*	0.0067	0.0093	0.0055
Other	0.0178	0.0099	0.0177	0.0099	0.0123	0.0081
Adverse Effects	-0.0037	0.0123	-0.0060	0.0122	-0.0078	0.0102
No. of Meds Prescribed	0.0065***	0.0010	0.0054***	0.0010	0.0049***	0.0008
Continued	0.0162**	0.0050	0.0189***	0.0050	0.0165***	0.0041
No Chronic Conditions	-0.0237***	0.0048	-0.0244***	0.0049	-0.0062	0.0038
Patient was referred	0.0070	0.0063	0.0095	0.0065	0.0056	0.0053
Reason for Visit: Acute	0.0130**	0.0046	0.0091*	0.0046	0.0003	0.0037
Past Visits (0)	0.0403***	0.0069	0.0376***	0.0068	0.0246***	0.0056
Past Visits (1-2)	0.0206***	0.0055	0.0182**	0.0054	0.0081	0.0045
Past Visits (3-5)	0.0231***	0.0053	0.0204***	0.0052	0.0138**	0.0042
Payment Source						
Private Insurance	-0.0270***	0.0058	-0.0269***	0.0058	-0.0108*	0.0047
Medicare	-0.0079	0.0057	-0.0108	0.0058	-0.0096*	0.0048
Medicaid	-0.0138	0.0074	-0.0136	0.0075	-0.0094	0.0061
Workers' Comp.	-0.0608**	0.0177	-0.0616**	0.0180	-0.0647***	0.0143
No Charge	0.0153	0.0266	0.0199	0.0261	0.0123	0.0218
Practice Characteristics						
Primary Care Physician	0.0150*	0.0061			-0.0000	0.0052
HMO Owns Practice	0.2234***	0.0291	0.2222***	0.0285	0.1690***	0.0254
Solo Practice	-0.0159*	0.0063	-0.0140*	0.0064	-0.0134*	0.0052
No Managed Care Contracts	-0.0226*	0.0093	-0.0257**	0.0095	-0.0179*	0.0079
Revenue: Medicare 50%+	-0.0221**	0.0082	-0.0222**	0.0084	-0.0093	0.0067
Revenue: Medicaid 50%+	-0.0082	0.0134	-0.0094	0.0134	-0.0137	0.0107
Revenue: Private Ins. 50%+	-0.0007	0.0072	0.0010	0.0074	0.0013	0.0061
Revenue: Patient 50%+	0.0182	0.0213	0.0240	0.0225	0.0112	0.0169
Constant	0.5018***	0.0353	0.5336***	0.0351	-0.0092	0.0571
Time FE	YES		YES		YES	
Drug Classes	YES		YES		NO	
Physician Specialties	NO		YES		NO	
Drug Controls	NO		NO		YES	
F-Stat	F(54, 5532) = 273.99		F(67, 5532) = 221.49		F(468, 5532) = .	
$\mathbf{R^2}$	0.2010		0.2035		0.4890	
N	61,295		61,295		61,295	
Method	OLS		OLS		OLS	

NOTE – Standard errors based on physician clusters. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Reference Variables – Northeast, Pov. 0-5%, White, Past Visits (6+), Self-pay.

prescribing. The finding of a small, consistent effect of variables that one would expect to affect the drug price-sensitivity of patients and physicians is suggestive of insurance-related moral hazard effects.

These findings hold when running the separate regressions by drug class. Patients with private insurance have lower generic prescribing rates in almost every regression (Table 7.1), although the statistical power of the tests are diminished due to decreased number of observations and only four out of the eight drug classes having statistically significant results (anti-infective agents, CNS agents, psychiatric agents and respiratory agents). Medicare, Medicaid and patients paying with worker's compensation also tend to show signs of moral hazard and decreased generic prescribing, but each were only statistically significant in one or two regressions at a 5 percent level.

Table 7.2: Test of Moral Hazard Due to Insurance Status Relative to Self-Pay Patients by Drug Classification using OLS Model

	Anti Infect.	CVD	CNS	Psych.	Met.	Horm.	Top.	Resp.
Private	-0.0525*	-0.02	-0.0341*	-0.055*	0.0062	-0.0147	-0.0044	-0.0881*
	(0.0143)	(0.0122)	(0.0121)	(0.0155)	(0.0175)	(0.016)	(0.0206)	(0.0304)
Medicare	0.0235	-0.0283*	-0.0215	-0.0391*	0.0012	0.005	-0.0046	0.0412
	(0.0163)	(0.0129)	(0.0118)	(0.0165)	(0.0184)	(0.0165)	(0.0206)	(0.0347)
Medicaid	-0.0337	-0.0203	-0.0228	-0.0549*	0.0128	-0.0243	0.0493	-0.0316
	(0.0176)	(0.0186)	(0.0136)	(0.0203)	(0.025)	(0.0235)	(0.0266)	(0.0336)
Workers' Comp.	-0.0721	0.0076	-0.0762*	-0.024	-0.0258	-0.027	-0.0531	0.2253*
	(0.0978)	(0.0815)	(0.02)	(0.0658)	(0.0949)	(0.0669)	(0.0687)	(0.1053)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
N	9859	10782	12658	6385	5383	4189	3928	3003

NOTE – Standard errors based on physician clusters in parentheses. * $p < 0.05$.
Same control variables as OLS Model (1) of Table 7.1, except for drug classification. Reproducing analytical methodology of Hellerstein (1998).
Drug Classes: Anti infective drugs, cardiovascular drugs, central nervous system agents, psychiatric agents, metabolic drugs, hormones, topical agents and respiratory agents.

Patients who were first time visitors to the practice received a generic prescription at a 4.0 percent higher level than patients who had been to the practice six or more times. This may reflect a couple of possible effects. First, it could be reflect the effect of patients who have a history with the doctor receiving the first prescription for a drug in the previous visit. Due to switching costs involved from going the brand-name to generic (and vice versa), this could mean that patients who received the prescription of the drug in the past, when they were more likely to be prescribed the brand-name, will stay with their initial prescription. Another possible explanation is that patients with a longer history with their physician may have more power to influence prescribing habits or willingness to express their desire for the brand-name form of

drug.

Because the data set does track whether the prescription was new or continued, we can make some assessment of the two hypotheses. The model estimates that continued prescriptions (rather than new) are prescribed as generics at a 1.6 percent higher level, evidence that patients switch from the brand-name to generic prescription. If there was no switching then patients with a continued medication should have a lower likelihood of being prescribed a generic, as they received their initial prescription earlier, assuming that this effect is not being driven by differences in case-mix (which is ruled out by the third OLS model). Thus, the first hypothesis, the time when the drug was first prescribed is what drives the effect of patient visit history, is not likely to be true. To truly rule out the first hypothesis, a regression with the interaction term of continued and a long-term patient (patient with six or more previous visits) is estimated. If the interaction term has explanatory power it would suggest that long-term patients are less likely to receive a generic prescription because they are receiving either a new or continued prescriptions. However, when this regression was estimated (not shown) the coefficient of the interaction term was insignificant (p = 0.96), suggesting that the effect of whether the prescription was new or continued is the same for long-term patients. While this does not conclusively prove the second hypothesis, it certainly suggests that the patient-physician relationship, measured by visit history, is an important characteristic in determining generic prescribing rates.

Table 7.3: Generic Prescribing Rate by Year and Generic Name Length

	Generic Prescribing Rate	
Year	**Generic Shorter**	**Generic Longer**
2006	0.6862	0.2001
2007	0.7052	0.2447
2008	0.7331	0.2609
2009	0.7827	0.2815
2010	0.7731	0.3540

The effects of the generic name and brand-name length are powerful predictor of generic prescribing, shown using a dummy for if the generic name is longer than the brand-name for each drug. The creation of this variable is based on whether the minimum length to write the generic name is more than the minimum length to write the brand-name form for a given

drug.[32] This measure, while imperfect of the true amount of effort it takes the physician (as it does not account for abbreviations unless an abbreviation is a valid code for a drug in the data set), still represents a highly statistically significant determinant of the generic prescribing rate. Drugs with a longer generic name have a 47.5 percent lower level of generic prescribing.

This finding may reflect the de-linked nature of a physician's prescription and what the patient actually has dispensed. Due to generic substitution laws, which allows for the substitution of the generic form of the drug in place of a brand-name prescription, physicians may have little incentive to prescribe the generic form of the drug as brand-name prescription will often be shorter (90.4 percent) and will give the patient the most flexibility in dispensing their preferred form of the drug. In addition, because the brand-name is often the originator product, writing the prescription for the generic form will have a switching cost associated as both the patient and physician get familiar to quality of the generic form of the drug (Hellstrom and Rudholm, 2010) and as the physician gets over the habituation formed by exclusively prescribing the brand-name. Additionally, it could just be that the shorter name of the drug, be it the generic name or brand-name, is easier to remember.

If this effect is due to the opportunity cost for writing a longer prescription, then it is conceivable to believe that drugs with shorter generic names are will have higher brand-name to generic switching rates. However, comparing the mean generic prescribing rate by year for drugs that have longer or shorter generic name suggest that the increase in generic prescribing rate has been greater (quicker) the drugs with longer generic name, albeit from a smaller baseline (Table 7.3). There is evidence in a plateau effect for generic prescribing rates as seen for the for shorter generic name drugs between 2009 and 2010, which plateaus at 78 percent. Further quantification of the role opportunity costs in prescription writing is analyzed in the Efficient Prescribing section utilizing variations in electronic prescribing.

7.2 Drug Characteristic Analysis

Certainly, the findings suggest that drug-specific effects (such as the drug name) play a role in generic prescribing habits. The strong effects of drug-specific characteristics warrant further

[32] Based on how it is coded in the NAMCS data set.

analysis for why these idiosyncratic behaviors in generic prescribing exist. The top forty drugs in the sample are analyzed, as they represent around 40 percent of all drugs prescribed and for which it is feasible to include drug market characteristics. In this section, two OLS regressions and a two-stage least squares (2SLS) regression are estimated for a subset of drugs that represent the top forty drugs prescribed in the 2006-2010 period to account for the influence of drug characteristics and market factors. As some a number of these drugs were approved off before January 1st, 1982, which is when the FDA first started to keep track of drug approval in the Orange Book, a dummy variable for drugs first brought market before this time is included in the regression model. In addition, because the NAMCS data set does not specify the formulation of the drug prescribed (i.e. strength, form of delivery or if it is an extended release formulation), a dummy for whether the drug has an extended release version on the market was included. Additionally, the first regression model included dummy for whether the drug is considered part of a narrow therapeutic index (NTI)[33] and the monopoly duration period enjoyed by the brand-name. In the second model, a measure of the familiarity of the generic drug by the public, using Google search trends from 2006-2010, was included to examine how the public's familiarity with the drug affects the physician's generic prescribing behavior. In the last model, in order to account for possible endogeneity of the public's familiarity of generics, a 2SLS regression is estimated, instrumented on monopoly duration period and whether the drug was brought to market before 1982.

Overall the three regression models give results for the non-drug market covariates included in the model that are very consistent with the findings from the baseline regression estimates using the full drug data set (Table 7.1). Notably, the regressions still finds evidence of moral hazard in generic prescribing for patients that have private insurance, Medicare and worker's

[33]Only two of the forty drugs in the sample were considered part of NTI lists that pharmacists cannot substitute from the physician's prescription (in a few states). These products are levothyroxine (i.e. Synthroid) and warfarin (i.e. Coumadin). Both of these drugs were prescribed more often as the brand-name form and so it is not surprising that the coefficient on NTI was negative in the models. Technically levothyroxine is not an NTI drug, but a search of the literature suggests that there are significant concerns about the therapeutic quality of levothyroxine substitutes (especially with regards to shelf-life) which led to an FDA notice in 1997. Warfarin (anti-coagulant) is an NTI due to the necessity for precise drug-concentration in the blood. It should be noted that a NTI classification does not mean the generic is of lesser quality - just that there is elevated risk that a slight difference between the generic and brand-name (due to manufacturing differences) could lead to adverse affects for patients.

Table 7.4: OLS and 2SLS Regression for Generic Prescribing Behavior with Drug Market Characteristics

Variable	**(1)**		**(2)**		**(3)**	
	β	**SE**	β	**SE**	β	**SE**
Payment Sources						
Private Insurance	-0.0173*	0.0086	-0.0154*	0.0077	-0.0154*	0.0078
Medicare	-0.0308**	0.0091	-0.0191*	0.0082	-0.0185*	0.0082
Medicaid	-0.0271*	0.0112	-0.0162	0.0103	-0.0153	0.0103
Workers' Comp	-0.1176***	0.0274	-0.1085***	0.0219	-0.109***	0.0218
Practice Characteristics						
HMO Owns Practice	0.1998***	0.0301	0.1978***	0.0289	0.1971***	0.0289
Solo Practice	-0.0128	0.0091	-0.0183*	0.0086	-0.0187*	0.0086
No MCC^{+}	-0.0202*	0.0098	-0.0192*	0.0093	-0.0191*	0.0093
Drug Characteristics						
Extended Release Form	0.0221**	0.0074	0.0388***	0.0070	0.0402***	0.0072
NTI Drug	-0.2432***	0.0144	-0.0132	0.0130	-0.0074	0.0161
Monopoly Duration (yrs)	-0.0191***	0.0006	-0.0018**	0.0005	Instrument	
Approved Pre-1982	0.103***	0.0106	-0.0039	0.0095	Instrument	
Generic's Search Pop.	–		1.0373***	0.0164	1.1159***	0.0327
Constant	-92.3732***	5.6591	-23.1671***	5.4876	-18.0528**	6.0345
Time FE	YES		YES		YES	
Regional FE	YES		YES		YES	
Physician Spec. Controls	YES		YES		YES	
Patient Controls	YES		YES		YES	
Drug Char. Controls	YES		YES		YES	
Endogenous Variable	–		–		Generic's Search Pop.	
Sargan Over ID Test	–		–		p = 0.0686	
First Stage R^2	–		–		0.7265	
First Stage F-statistic	–		–		3,542	
D-W-H Test	–		–		p = 0.0067	
R^2	0.3108		0.4427		0.4432	
N	22,590		22,590		22,590	
Method	OLS		OLS		2SLS	

NOTE – Standard errors based on physician clusters. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2SLS tests (Sargan test of over identification and Durbin-Wu-Hausman test of exogeneity) are calculated with normal standard error assumptions.
Reference Variable – Self-pay. Other variables included in regression (not shown for sake of brevity) include controls for region fixed effects, patient characteristics, other payment sources, and practice characteristics. Regression specification is similar to that of Table 7.1.
$^{+}$No MCC is no managed care contract.

compensation. As before, the regressions also find that practices owned by HMOs are much more likely to prescribe generics and practices that do not have any managed care contracts are less likely to prescribe generics.

The first model suggests that the generic prescribing rate for a drug is reduced by longer market exclusivity durations and if the drug is an NTI. The market exclusivity period for the brand-name (average length is 9.58 years) reduces generic prescribing by around 1.9 percentage points for each additional year of monopoly duration. This effect is small relative to the exogenous 4.6 percentage points increase in generic prescribing. Drugs that are classified as NTIs are prescribed as generics at a 24.3 percent lower level, perhaps due to concerns about the quality or adverse effects from the generic. However, drugs that were approved before 1982 are prescribed as generics at a 10.3 percent higher level, as are drugs that have extended release forms[34] at a 2 percent higher level. It is likely that both of these measures have a positive effect on generic prescribing because they tend to represent older drugs that physicians have had time to adopt the generic.

The second OLS model includes a measure for the public's familiarity with the generic drug as measured by Google search trends during the sample period.[35] While it is not unexpected that this measure correlates well with the general generic prescribing rates of physicians, the degree of which this variable correlates with the generic prescribing trends is astounding - with the regression estimate suggesting that on average, for every one percent increase in generic drug search share, there will be a 1.0 percentage point increase in generic prescribing. Of course, endogeneity is a major issue. Search trends could directly affect generic prescribing if physician prescribing habits are affected by how familiar the public is to the generic drug or could be due to patients searching the prescriptions written by the physician (reverse causality).[36]

The coefficients on monopoly duration length and approval before 1982 are significantly reduced. While the monopoly duration coefficient remains significant, it is of little economic

[34]Usually drugs for which the original formulation was approved earlier.

[35]Remember that this variable is defined as the share of Google searches by the generic name divided by the sum of the searches for the generic and brand-name names (quarterly average).

[36]However, lagged search trends are actually more significant in explaining the variance in prescribing habits (higher R^2), with a five-quarter lagged generic search share having the most explanatory power, suggesting that physician prescribing habits lags public familiarity with the generic.

significance. This suggests the possibility that monopoly duration and approvals before 1982 are not actually direct predictors for generic prescribing habits, but were merely significant (economically and statistically) in the first regression model due to omitted variable bias; instead these variables may instead derive their impact due to their effect on the public's familiarity with the drug. Thus, they may be appropriate variables to instrument on. This regression is shown in model 3. Though previous studies have used monopoly duration as an exogenous measure of habituation and branding (Berndt et al., 1995), it is not clear that it is a truly exogenous measure of physician habituation, but rather capturing public familiarity with the generic. Using a 2SLS regression, the generic's search popularity was instrumented on monopoly duration and whether the drug was approved before 1982.[37] The results of the 2SLS regression model suggest that the effect of a one percentage point increase in the generic search popularity will increase generic prescribing rates by 1.1 percentage points.

The choice of the instrument is statistically valid. The Sargan's test for overidentification[38] has a p-value = 0.0686, which suggests that the null hypothesis of valid instruments cannot be rejected at the 5 percent level. Furthermore, the first-stage $R^2 = 0.7265$ (F-test >> 10), suggests the instruments were not weak. Lastly, the Durbin-Wu-Hausman test for exogeneity rejected the null hypothesis that the generic search popularity is consistently estimated between the OLS and 2SLS regression models at the 5 percent level (suggesting that the measure is endogenous). To further test that the generic search popularity was causal on physician prescribing habits, lagged (and leading) generic search popularity variables were created and regressed as an independent covariate. The best fitting generic search variable was a five-quarter lagged variable (i.e. the relative search popularity for the generic five-quarters before the patient encounter in which the drug was prescribed).[39] This finding further suggests that physicians are influenced by the

[37] These instruments may not be theoretically great, indeed the literature has found evidence of physician habituation(Berndt et al., 1995). However, the in favor of valid instruments is that the habituation that has been found may not be due to physicians habituation, but that physicians have little incentive to change their prescribing habits if the public is not aware or familiar with the generic. That is, market exclusivity affects the public's familiarity with the generic, which in turn affects the physician's prescribing habits.

[38] Also known as the Hansen test or J-test for over identifying restrictions.

[39] Although the t-statistic could be biased for the lagged variables duet to the secular increase in generic prescribing with respect to time and the fact that generic search popularity tended to be higher than the average generic prescribing rates in a given quarter, the R^2 of the regression models should not be biased as they are measure of how well the independent variable explains the variance in the dependent variable (reduced residuals).

public's familiarity with the generic drug and may in fact lag behind the public with respect to the adoption of generics in their prescriptions.

Physicians are sensitive to patent expiration in their prescribing habit. However, they greatly lag the dispensing of generic drugs due to generic substitution laws. For example, in the selective serotonin reuptake inhibitor (SSRI) antidepressant drug market, after the introduction of generic sertraline (Zoloft) in June 2006, there was a 10 percent increase in generic dispensing of SSRI drugs within 3 months (Ventimiglia and Kalali, 2010), almost all of which is attributable to the widespread generic dispensing of sertraline (likely around 90 percent dispensing of generic). However, even in 2010, the physician generic prescribing rate of sertraline was only 26.6 percent, up from 2 percent in 2006.

7.3 Efficiency of Prescribing, Primary Care Physicians vs. Specialists

The de-linkage between the prescription and dispensing of a drug, makes it difficult to understand the significance of the determinants of physician generic prescribing in terms of the impact on the healthcare system. While it may be true that certain factors can influence physician behavior and cause them to prescribe the brand-name form, it does not necessarily follow that the patient will have the brand-name dispensed. One way to mitigate the de-linkage problem is to reduce the heterogeneity in the data and analyze the prescribing habits by drug class. This analysis can shed insight on a topic of particular concern: the differences between the prescribing habits of primary care physicians and specialists (i.e. "efficiency of prescribing"). Fundamentally, are primary care physicians managing cases the same way as specialists in terms of generic prescribing? Thus, in this study, "efficiency of prescribing" is whether generic prescribing rates differ between primary care physicians and the relevant specialist[40] for the same set of drugs. Because there have been some contradictions in the literature about whether the increased generic drug usage is due to primary care physicians, through the primary care drug class, or whether specialists prescribe generics at higher rates due to increased knowledge of generics, it is of use to examine the generic drug prescribing habits among the two types of physicians.

[40] For example, cardiovascular specialist for cardiovascular drugs.

Four characteristic drug classes are chosen (cardiovascular drugs, hormones, psychiatric agents, and central nervous system (CNS) agents) and the prescribing habits of primary care physicians are compared with the prescribing habits of the corresponding specialist that prescribed that particular drug class the most (cardiovascular, OBGYN, psychiatry and neurology, respectively). These drug classes are chosen as they are they are they represent the most popular drug classes that were prescribed by both primary care physicians and (generally) a single specialty.

Table 7.5: Logistic Regression for Efficient Prescribing, Four Drug Class and Specialties

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	β	β	β	β	β	β	β	β
Year	0.0521***	0.0435***	0.0224**	0.0199**	0.0246**	0.0304***	0.0172***	0.029***
	(0.0045)	(0.0036)	(0.0067)	(0.0061)	(0.0075)	(0.0056)	(0.0047)	(0.0047)
Combination	-0.2876***	–	O	–	O	–	-0.2173***	–
	(0.0581)						(0.0191)	
G<B x Elec. Rx^{+}	-0.0919*	–	O	–	O	–	-0.0267	–
	(0.0427)						(0.0485)	
B<G x No Elec. Rx	-0.5719***	–	-0.7544***	–	-0.5744***	–	-0.2217***	–
	(0.0245)		(0.0705)		(0.0448)		(0.0288)	
B<G x Elec. Rx	-0.546***	–	-0.7075***	–	-0.5037***	–	-0.1558***	–
	(0.0262)		(0.072)		(0.0495)		(0.0298)	
Private Insurance	-0.0331*	-0.0228*	-0.0137	-0.0075	-0.0547**	-0.0361*	-0.0123	-0.0047
	(0.0146)	(0.0115)	(0.0238)	(0.0223)	(0.017)	(0.014)	(0.0141)	(0.0127)
Medicare	-0.0374*	-0.0219	-0.0423	-0.0403	-0.036	-0.0209	-0.0223	-0.0024
	(0.0158)	(0.0132)	(0.0255)	(0.0243)	(0.0189)	(0.0156)	(0.014)	(0.0127)
Medicaid	-0.0037	-0.0105	-0.0454	-0.0198	-0.0564*	-0.0415*	-0.0017	-0.0019
	(0.0216)	(0.0174)	(0.0345)	(0.0323)	(0.0227)	(0.0193)	(0.0158)	(0.0145)
No Managed Care Contracts	-0.0772***	-0.0521***	-0.048*	-0.0448*	-0.0008	0.009	-0.0456**	-0.0288*
	(0.0168)	(0.0136)	(0.0211)	(0.019)	(0.0216)	(0.0183)	(0.0135)	(0.0134)
Primary Care Physician	0.0387*	-0.0009	0.0324	0.0712*	0.0301	-0.0067	0.0418*	-0.0059
	(0.0171)	(0.0156)	(0.0294)	(0.0285)	(0.0206)	(0.0176)	(0.0169)	(0.0178)
Drug Controls	NO	YES	NO	YES	NO	YES	NO	YES
Baseline Regression Controls	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.1579	0.4273	0.3164	0.4581	0.1173	0.393	0.1086	0.2459
Log Pseudo LL	-4100	-2753	-735	-655	-2701	-1429	-3082	-2545
N	7047	6966	1863	1916	4722	4772	7186	6910
Drug Class	**CVD**		**Hormones**		**Psych Agents**		**CNS Agents**	
Specialty (Comparison)	**Cardiovascular**		**OBGYN**		**Psychiatry**		**Neurology**	
Mean GPR	**53.3%**		**32.0%**		**19.7%**		**18.7%**	

NOTE – Marginal effects of logit model presented. For continuous variables, calculated at mean. Standard errors based on physician clusters in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

$^{+}$G<B x Elec. Rx is shorthand for generic name shorter than brand name and physicians has electronic prescribing. Others follow by similar logic. Reference Variables – G<B x No Elec. Rx, Self-pay. Other variables included in regression (not shown for sake of brevity) include controls for region fixed effects, patient characteristics, other payment sources, and practice characteristics. Regression specification similar to that of Table 7.1.

Two logit regressions for each of the four drug classes and physician specialties are estimated. The first logit regression is similar to first baseline regression model (model 1, Table 7.1), but with an interaction term on the dummy variable for the length of the drug name with whether the physician has electronic prescribing.[41] The second logit regressions includes drug controls (recreation of model 3, Table 7.1) to control for drug idiosyncratic and case-mix effects that may account for differences between primary care physician prescribing and specialty prescribing (i.e. the difference in generic prescribing rates is due to what drugs are being prescribed). The second model can be considered over controlled as it controls for the physician's decision in choosing which drug to prescribe, however, it should find the average differences in generic prescribing habits between specialists and primary care physicians among the same drugs.[42] However, because the purpose of this study is to examine the decision to prescribe the generic condition on the choice of the drug, this over controlled specification is still a valid estimate for the differences between primary care physician and specialist prescribing.

The regression estimates find that there is a 1.7 to 5.2 percent increases in the level of generic prescribing by year for each drug class (Table 7.5). There is a 2.2 to 5.4 percentage point reduction in generic prescribing for cardiovascular and psychiatric agents for patients with private insurance relative to self-pay patients. In addition, there is a 3 to 8 percent reduced level of generic prescribing in practices with no managed care contracts for cardiovascular agents, hormones, and CNS agents. The addition of drug dummies does not erode the significance of these findings.

The effect of electronic prescribing on generic prescribing is quite significant. Electronic prescribing mitigates the effect of the generic name being longer than the brand-name on generic prescribing by around 3 to 7 percentage points. Although electronic prescribing systems differ, physicians with electronic prescribing can generally choose a desired drug from a drop down menu after typing the first few letters of the drug name, and need not write the entire drug

[41] This interaction term was not included in the baseline regression because of the possible effects of heterogeneity in the availability of electronic prescribing among physicians in different specialties or settings. By limiting analysis to certain drug classes and physician specialties the effect of this heterogeneity and selection issues are mitigated.

[42] For example, a specialist may have more knowledge on a newer, more specialized drug. These drugs may have different market characteristics (off patent more recently), which could account for differences in generic prescribing habits independently from differences between specialist and primary care physician.

name out. Physicians without electronic prescribing would have to write out the entirety of the drug name when writing the prescription. The interaction terms for the generic name being longer than the brand-name dummy with whether the practice has electronic prescribing are statistically significant. Essentially, the effect of electronic prescribing is to reduce the effect of the differences in length for the generic and brand name. Physicians with electronic prescribing are less likely to prescribe the generic if it is shorter than the brand-name compared to physicians without electronic prescribing. Physicians with electronic prescribing are also more likely to prescribe the generic if it is longer than the brand-name compared to physicians without electronic prescribing. This finding suggests that the effect of electronic prescribing partially mitigates the effect if the length of the drug name in both directions. While there may be some concern that the types of physicians that would have access to electronic prescribing are different than physicians who do not have access to electronic prescribing, the fact the effect of the length of the drug's generic name and brand-name are reduced in both directions suggests that this is truly capturing the time-costs to physically write a prescription.

In terms of "efficiency of prescribing," primary care physicians have a 3 to 4 percentage points higher rate of generic prescribing. However, after drug dummies were included this effect was completely eroded, except for hormones. Much of the difference between the prescribing habits of primary care physicians and specialists is due to differences between the case-mix of drugs prescribed. A chi-square test for association for primary care physicians and specialists case-mix of drugs prescribed finds the case-mix were not comparable for each of the drug classes with all $p << 0.001$ (Table A.7).

The higher generic prescribing rate of primary care physicians can be attributed to greater generic prescribing among the "primary care drug class," consistent with the findings of Aitken et al. (2009), who found that the increase in generic drug usage has been among the primary care drug class where there has been a concerted effort by insurers and policy makers to promote generic usage. It would also reconcile the (seemingly contradictory) finding that specialists were more likely than non-specialists to prescribe antimicrobial drugs in the generic form (Howard, 1997). While there is no evidence that specialists prescribed generics at a higher rate, it certainly looks like there are on average no differences between primary care physicians and specialists

when controlling for the drug prescribed. The only exception is for hormones, where primary care physicians prescribe drugs as generics at 7 percent higher level compared to OBGYNs after including drug controls.

7.4 HTPS and Industry Influence

In order to evaluate how physicians perceive their own generic prescribing habits and the role of industry influence in comparison with their actual prescribing habits, the Health Tracking Physicians Survey (HTPS) data set is used. Three ordered logit regressions, shown in Table 7.6, are specified with physicians and practice controls, and for different measures of industry influence. In the first regression, dummies are included for whether the physician indicated that they received free food, speaking honoraria, conference travel or compensated admission into a CME conference. These measures represent the set of industry influences that were most significant or could be characterized as the most ethically compromising.[43] The second regression model includes a variable that represents the total number of admitted industry influences (maximum of 8). The final regression model estimates the effect of the admitted yearly financial compensation[44] that the physician received from the drug and medical device industry. For each of the ordered logit regressions, the odds-ratios and 95 percent confidence intervals are reported. The odds-ratio represents the effect of the independent variable on the odds of the physician self-reporting a higher level of generic prescribing (i.e. changing their rating from a 4 to a 5, etc). The odds-ratio should not be interpreted as a measure of the relative or proportional effect, only as a measure of effect size.

The regression models had similar findings for the effects of physician and practice characteristics. Specialty physicians professed lower generic prescribing habits than internal medicine physicians, with odds-ratios for the physician admitting to a higher level of generic prescribing ranging from 0.39 to 0.74 (all $p < 0.01$), while pediatricians had higher generic prescribing with an odds-ratio of 1.38 ($p < 0.01$). Among practice types, physicians in HMO practices were significantly more likely to say they prescribe generis (OR = 2.09, $p < 0.001$); however, practices

[43] As opposed to free drug samples or honoraria for filling out surveys.

[44] Data was reported in five categories - None, $1 to $500, $501 to $1000, $1001 to $5000, and greater than $5000.

Table 7.6: Ordered Logit Regression for the Determinants of Self-Assessed Generic Prescribing, HTPS 2008

	(1)		(2)		(3)	
Variable	**OR**	**95 % CI**	**OR**	**95 % CI**	**OR**	**95 % CI**
Specialty						
Fam. Practice	1.012	0.84-1.21	1.005	0.83-1.21	0.981	0.81-1.18
Pediatrician	1.375**	1.08-1.74	1.39**	1.09-1.76	1.357*	1.07-1.72
Medical Spec.	0.742**	0.61-0.89	0.72***	0.59-0.86	0.722***	0.60-0.86
Surgical Spec.	0.737**	0.60-0.90	0.732**	0.59-0.89	0.739**	0.60-0.90
Psychiatry	0.387***	0.29-0.51	0.377***	0.28-0.49	0.386***	0.29-0.50
OBGYN	0.651**	0.50-0.84	0.653**	0.50-0.85	0.645**	0.49-0.83
Practice Type						
Group	1.152*	1.00-1.31	1.138	0.99-1.30	1.149*	1.00-1.31
HMO	2.091***	1.45-2.99	2.134***	1.48-3.06	2.303***	1.62-3.27
Med. School	1.113	0.85-1.44	1.08	0.83-1.39	1.181	0.91-1.51
Hospital	1.186	0.95-1.47	1.172	0.94-1.44	1.259*	1.02-1.55
Other	1.222	0.89-1.66	1.25	0.91-1.70	1.28	0.93-1.74
Phys./Pract. Char.						
Female	0.804**	0.70-0.91	0.82**	0.71-0.93	0.796**	0.69-0.90
Hrs of Charity Care	1.009*	1.00-1.01	1.008*	1.00-1.01	1.009*	1.00-1.01
Black Patients (0-100)	0.997	0.99-1.00	0.997	0.99-1.00	0.998	0.99-1.00
Hisp. Patients (0-100)	1.002	0.99-1.00	1.002	0.99-1.00	1.003	0.99-1.00
Min. Health Educ.	1.195**	1.05-1.34	1.186**	1.05-1.33	1.2**	1.06-1.35
No MCC^{+}	0.996	0.81-1.20	0.985	0.81-1.19	1.042	0.85-1.26
Electronic Rx	1.233**	1.09-1.39	1.228**	1.08-1.38	1.251***	1.11-1.40
Industry Influence						
Free Food	0.758**	0.64-0.88		–		–
Speaking Honoraria	0.882	0.73-1.05		–		–
Conference Travel	0.633***	0.53-0.75		–		–
CME Admission	0.809*	0.65-0.99		–		–
No. of Indus. Infl.		–	0.847***	0.81-0.88		–
Comp. ($1-$500)		–		–	0.761***	0.67-0.86
Comp. ($501-$1000)		–		–	0.635***	0.51-0.78
Comp. ($1001-$5000)		–		–	0.541***	0.42-0.68
Comp. ($5000+)		–		–	0.402***	0.29-0.54
Cuts						
Cut 1	-5.37	-5.80, -4.93	-5.36	-5.77, -4.95	-5.15	-5.54, -4.75
Cut 2	-4.22	-4.57, -3.87	-4.22	-4.54, -3.89	-4.00	-4.30, -3.68
Cut 3	-2.31	-2.62, -2.00	-2.31	-2.59, -2.02	-2.09	-2.35, -1.82
Cut 4	0.26	-0.03, 0.562	0.25	-0.01, 0.529	0.48	0.215, 0.736
Pseudo R^2	0.0284		0.0273		0.0265	
Log Pseudo LL	-4748		-4736		-4775	
N	4507		4486		4521	

NOTE – Robust standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

$^{+}$No MCC means the practice had no managed care contracts.

Reference Variables – Internal Medicine, Solo Practitioner, $0 Compensation.

Survey asked physician's about their behavior in 2006. The industry compensation is yearly total.

with managed care contracts did not have different prescribing habits. Physicians who attended educational seminars to improve minority health showed higher self-assessed generic prescribing (2 percentage points), however, there is no difference in self-assessed generic prescribing habits based on the race of the patients seen at the practice. Physicians with electronic prescribing had higher admitted generic drug prescribing (OR = 1.23, $p < 0.01$). This finding may be reflective of the fact that the physicians who have access to electronic prescribing, may have more advanced practices and knowledge on generic drugs or that electronic prescribing makes prescribing generic drugs easier.[45]

The effect of industry influences of in the form of free food, conference travel and CME admissions all lower the level of physician's self-assessed generic prescribing, with odds-ratios of 0.76, 0.63, and 0.81, respectively. Speaking honorarias did not affect the level of generic prescribing at the 5 percent level. The number of admitted industry influences has a negative impact on the level of generic prescribing (OR = 0.85, $p < 0.001$). Lastly, the total compensation received has a significant impact on self-assessed generic prescribing. Compared to physicians with no self-reported compensation from drug and medical device companies, physicians who received over $5000 in compensation have a 60 percent reduced odds in their self-assessed generic prescribing level ($p < 0.001$). The amount of compensation is directly related to the reduction in the level of generic prescribing, with lower odds-ratios at higher compensation levels.

While the models show clear evidence the physicians with industry influence have a reduced propensity to prescribe generics, it cannot necessarily prove that industry influence has a direct (causal) impact on generic prescribing. Endogeneity due to self-selection bias is of great concern in this scenario - physicians who have a lot of industry influences (especially those that receive paid travel to conferences or speaking honoraria), may already be more skeptical of generics than their peers. However, these findings still raise significant questions about potential for physician conflict of interests that could reduce patient welfare and increase healthcare costs, as drug companies could improperly influence physician behavior in a manner that serves the physician's financial interests instead of the patient's clinical and economic interests.

[45]This effect was also seen in the NAMCS data set.

8 Discussion

8.1 Findings

The findings from this study suggest that physician prescribing habits were affected by a number of causes, such as: industry influence, practice characteristics, drug idiosyncratic characteristics, public familiarity with the generic drug, electronic prescribing, and patient financial characteristics (summarized in Table 8.1). Furthermore, there were very little difference between the generic prescribing habits of primary care physicians and specialists, except for the prescribing of hormones between primary care physicians and OBGYN specialists. Some of the findings, especially the strong impact that industry influence on the physician's self-assessed generic prescribing habits warrant concern. The characteristics and incentives that explain physician prescribing habits can be reduced into a few fundamental categories: direct economic and financial incentivizes, patient-dependent behavior, information related behavior and idiosyncratic, drug-based behavior (Table 8.1).

A number of measures suggest that physicians were affected by economic and financial incentives, both at the practice and physician level. Most significantly, physician's in HMO owned practices were more likely to prescribe generics and self-report that they prescribe generics at a higher rate. This finding may be reflective of the fact that HMOs have strong financial incentives for the use of generic medicines and push physicians to prescribe generics. Indeed, this effect hold true even in practices without direct ownership incentives, as physicians without any managed care contracts prescribe generics at lower rates than those with at least one managed care contract. Physicians who received greater financial compensation from industry sources, had a self-assessed lower generic prescribing rate, which may suggest that either physicians are either influenced by direct financial considerations or where they receive information with regards to generic drugs and prescribing.

One of the most surprising findings, however, has been the differences in generic prescribing habits for drugs with a generic name that is shorter than the brand-name versus those drugs that have a generic name that is longer than the brand-name. As differences in quality of the generic form of a drug is unlikely to be systematically related to the differences in the generic

name length and brand-name length, it is puzzling to understand this finding in terms of clinically relevant determinants of generic prescribing habits. However, an argument can be made for numerous non-clinically relevant, but economically relevant, incentives. The differences in generic prescribing rates could be due the fact that physicians fall into an "equilibrium," in which drugs are prescribed in certain form (either generic or brand-name) based on standard industry practices. The causes for why different drugs fall into different equilibrium prescribing rates are presumably numerous factors, such as the assessment of the quality of the generic substitute, the effects habituation and marketing at both the patient and physician level, or even, perhaps surprisingly, the time-costs associated with prescribing a longer named project. It is unlikely that the latter effect accounts for the entirety of the difference in generic prescribing rates. Utilizing variations in practice electronic prescribing status, where one would expect that the time-cost for prescribing a drug due to the length of the drug would be mitigate, an estimate of the effect on the drug name on the time-cost of prescribing were calculated. The regressions found that the effect of the electronic prescribing was to reduce the effect of the length of the drug by 2.2 to 9.2 percentage points, depending on the drug class. As the effect of electronic prescribing was to reduce the generic prescribing rate for drugs with a shorter generic name than brand name and increase the generic prescribing rate for drugs with a longer generic name than brand name compared with practices without electronic prescribing, this finding strongly suggests that the time-costs associated with prescribing can account for some difference in generic prescribing between different drugs. A conservative, lower-bound estimate suggests that 4.5 percent of the effect can be attributed to time-costs (and perhaps as much as 12 percent of the effect).[46] The rest of the effect presumably can be attributed to habituation, branding, industry-wide habits, and patient-dependent behavior.

Indeed, informational characteristics seem to play the most significant role in generic prescribing habits. Google search data (a measure of public's information, knowledge, and name-usage) was an extremely good predictor of generic prescribing for the top forty most popular drugs in the data set. While, endogeneity is a major concern, the results were only more signif-

[46]Calculations based on the regression in Table 7.5 from the ratio of the difference between the coefficients between practices with electronic prescribing and those without electronic prescribing for drugs with brand-names shorter in length compared to their generic names.

icant when instrumented on market exclusivity length for the drug and whether FDA approval was granted before 1982. Quarterly lagged measurements were also a better fit for the generic prescribing decision, suggesting that physicians follow the general public in terms of awareness and usage of the generic to some degree. Furthermore, evidence of information diffusion was found with generic prescribing rates showing a strong increase over the five-year data period, likely a function of increasing knowledge of the existence and quality of generics. Regional differences in prescribing may also be attributable to differences in the rate of information diffusion.

The source of physician information on generic medicines is very important as well. The results from Medco's[47] 2006 Drug Trend Report, found that more physicians thought that generics were not chemically equivalent, were less effective, had more side effects, and were less safe compared to patients and pharmacists.[48] The differences in perceptions of the quality of generics may be directly attributable to the sources of information on generic medicines for physicians, patients and pharmacists. Physicians who had greater a greater number of industry influences, were less likely to prescribing generics, while physicians who had managed care contracts were more likely to prescribing generics. The role of pharmaceutical sales representatives and other industry influences on generic prescribing may not be through direct financial motivations, but rather a reflection of the information on generics that physicians receive (which may or may not be accurate). The effect of increased generic prescribing rates in practices that were HMO-owned and those with at least one managed care contract could be due to greater communications by managed care companies for the use of generic medicines. This conforms with the findings of an AARP survey of physicians, which found that 80 percent of physicians find out about the availability of generic medicines from insurers or pharmacy benefit managers (Barrett, 2005). Electronic prescribing may also alert the physician to new generic drugs and formulary information, boosting generic prescribing rates significantly (Purvis, 2008). The patient's familiarity with generics may also represent an important informational source.

Lastly, there seems to be strong evidence that patient insurance status affects the generic

[47]Medco (now Express Scripts) is one of the largest pharmacy benefit managers.

[48]Between 19 to 27 percent of physicians believed these "misconceptions," compared with 8 to 17 percent of patients and 5 to 8 percent of pharmacists.

prescribing habits of physicians. Patients with private insurance, and to a lesser degree Medicare, have a small, but statistically significant, reduction in generic prescribing relative to self-pay patients, suggesting evidence of moral hazard. Interestingly, past literature has found only mixed evidence for differences in generic prescribing between patients with insurance and self-pay patients, suggesting that is a more recent development (Hellerstein, 1998; Howard, 1997; Rice, 2011). A recent survey of physicians found that 37 percent of doctors said they acquiesce to patient branded drugs requests (Campbell et al., 2013). Physicians who had more interactions with drug industry representatives were more likely to acquiesce.

Table 8.1: Summary of Findings and Economic Interpretations

	Variable	NAMCS	HTPS	Economic Interpretation
1	Region	Varies	–	Information diffusion
2	Time	GPR ↑	–	Exogenous increase in generic usage
3	Insurance status	GPR ↓	–	Patient dependent prescribing, moral hazard
4	HMO ownership	GPR ↑	GPR ↑	Financial incentive, informational effect
5	Managed care contracts	GPR ↑	No effect	Financial incentive, informational effect
6	Visit history	GPR ↓	–	Physician-patient relationship
7	Continued medications	GPR ↑	–	Switching to generic
8	Patient characteristics: Male, Black, Hispanic	GPR ↑	No effect	Patient dependent prescribing
9	Drug name length generic > brand-name	GPR ↓	–	Branding, habituation, opportunity costs
10	Electronic prescribing	Varies	GPR ↑	Opportunity costs reduced, informational effects
11	Narrow therapeutic index	GPR ↓	–	Quality, risk-averse prescribing
12	Monopoly duration	GPR ↓	–	Branding, familiarity: manifests in public's generic familiarity
13	Public generic familiarity	GPR ↑	–	Patient dependent prescribing, phyicians follow public familiarity
14	Primary care physician	No effect	GPR ↑	Drug case-mix determines GPR
15	Drug idiosyncracies	Varies	–	Standardization, branding, habituation, information, etc.
16	Industry influence	–	GPR ↓	Financial incentive, informational effect
17	Generic substitution laws	–	–	De-links prescribing and dispensing

NOTE - GPR is the generic prescribing rate.

8.2 Policy Implications

While physician education on novel drug products by industry sales representatives is necessary to a certain degree (e.g. for the accelerated adoption of novel therapeutic agents that could promote patient health), public health officials must be wary that this relationship could cross

ethical boundaries. In particular financial compensation in the form of free food, free travel, and other gifts could compromise the physician's ability to act as the patient's agent. However, bans on drug representative detailing could in fact do more harm than good by reducing physician knowledge on new drug products (Huddle, 2008). Instead, the effects of unethical behavior, inaccurate information or perceptions about the quality of generic medicines can be mitigated by academic detailing (university or non-commercial-based educational outreach), better medical school training guidelines for how to properly handle industry detailing and compensation derived from such interactions, as well as greater transparency of any compensation through public disclosure[49] so that patients are aware of such external influences.

Furthermore, this study's findings suggest that physicians are heavily influenced by drug idiosyncrasies in prescribing generics. There is a bimodal distribution for the average generic prescribing rates for a given drug in the NAMCS data set, suggesting a drug is generically prescribed as either a generic or brand-name. One of the best predictors for generic prescribing rates is whether the generic name is longer than the brand-name alternative, indicating that generic prescribing habits may not be due to the "quality" of the generic, but rather how much effort it takes to write a prescription and the powerful effects of branding. Academic detailing could be used to promote greater general usage of the generic name, to reduce the effect of branding due to industry-standard name usage. Greater adoption of electronic prescribing software can reduce the time-costs associated with prescribing a longer drug name and allow physicians to keep up-to-date on the introduction of generic drugs and new formularies. Generic substitution decision support on electronic prescribing has been shown to greatly increase generic prescribing across all specialties compared to hand-written prescriptions (Stenner et al., 2010). Physicians also seem to be influenced by the public's familiarity of the generic drug name, which suggests that accelerating the generic's name into general usage, through patient education programs, will also result in increased generic prescribing rates.

Moral hazard in generic prescribing was consistently found in this study and although generic substitution laws and co-pays could mitigate much of the difference in generic prescribing when

[49]The Physician Payment Sunshine Act as part of the Patient Protection and Affordable Care Act will mandate such reporting to the Department of Health and Human Services beginning in 2012 (with first reports due March 31, 2013).

the drug is actually dispensed, policy makers may wish to further study if the difference in prescribing persists to the dispensing of the drug. Insurance companies and pharmacy benefit managers play an important role in promoting generic drug usage. It is likely that HMO physicians prescribe generics at higher rates due to not only financial considerations, but also increased knowledge about generic drug availability as a result of generic usage promotions from insurance companies. Unfortunately, physicians seem to absent from the decision to use generics as the majority of the decision to use the generic is during the pharmacy dispensing due to generic substitution laws (see sertraline/Zoloft patent expiration example). The initial period after the entrant of a generic, would be a potent period for the promotion of generic usage, where physicians could update their patient prescriptions to reflect what is actually being dispensed. Electronic prescribing software that links the prescription and dispensing of a drug could be an invaluable service for better case-management.

While both the NAMCS and HTPS data sets find strong differences in generic prescribing rates by specialty, after controlling for the drugs prescribed, there was no differences in generic prescribing among three of the four classes of drugs examined (cardiovascular drugs, psych agents and CNS agents). Although previous literature has found some evidence that specialists were more likely to prescribe generics (Howard, 1997), this study finds no differences, suggesting that primary care physicians are just as knowledgeable about the existence and quality of generics and efficient in generic prescribing as specialists.

8.3 Study Limitations and Future Explorations

This study extensively examines physician characteristics that determine generic prescribing habits and explores the role of drug market characteristics for a large subset of drugs using the publically available data sets. However, this study suggests that a greater exploration of the role of the drug name (generic versus name-brand), electronic prescribing and the public's familiarity with the generic on the physician prescribing behavior is necessary. Future studies could use the restricted NAMCS and HTPS data sets (which has geographic identifiers) to examine the effect of variations of generic substitution laws and formularies. Furthermore, geographic identifiers could be used to match regional variations in industry influence, using

publically available physician compensation data, and the public's generic familiarity to account for regional differences in generic prescribing.

As physician, patient and drug characteristics were found to have an impact on prescribing habits, a study of how such differences actually translates into generic drug usage would be of great interest to policy makers. A more in-depth analysis of the role of information and quality may help elucidate why strong drug idiosyncrasies in generic prescribing habits exists. For example, this study suggests that the effect of monopoly duration on branding, found in previous literature, may actually affect public familiarity with the generic drug, instead of as a direct mechanism of influencing physician behavior through habituation. Thus, the effect of public familiarity and acceptance of the generic on prescribing habits merits further exploration, using a more refined measure of public familiarity than Google search trends.

9 Conclusion

The goal of this study is to examine the determinants of generic prescribing practices of physicians in the larger context of understanding the physician decision making process. This study focuses on the decision to prescribe the generic or brand-name form of the drug, which is generally considered to be clinically equivalent. Generic substitution laws de-link the decision to use the generic from what the physician prescribes and may limit the ability to make broad conclusions about the implications of physician prescribing on healthcare savings. However, analyzing the incentives and characteristics that effect physician generic prescribing is still important to understand why physicians are "over-prescribing" brand-name drugs. In general, these findings can be characterized into four main categories: (1) financial/economic, (2) informational, (3) patient-dependent and (4) drug idiosyncratic effects.

A number of observable characteristics about the patient, physician, and drug, influence the decision to prescribe a drug as a generic or brand-name are found using the National Ambulatory Medical Care Survey, 2006-2010. Broadly, there are strong drug-specific idiosyncratic effects and drugs are predominantly prescribed in either the generic or brand-name form (bimodal distribution). The effect of a drug having a longer generic name than brand names on generic

prescribing habits is dramatic, resulting in a reduction in generic prescribing rate by 47.5 percentage points. Part of this effect may be due to the effort it takes for the physicians to write the prescription, as physicians with electronic prescriptions do not have as large of a reduction in generic prescribing rates for drugs with longer generic names. The Google search popularity for the generic drug (relative to brand-name) has nearly a one-to-one relationship with generic prescribing habits.

Patients seem to show some degree of price-sensitivity to generic medicines. Patients with private insurance, Medicare, and worker's compensation are consistently less likely to be prescribed a generic compared to patients who are self-pay. This finding suggests evidence of moral hazard in prescribing, which has been inconsistently found in previous literature analyzing the NAMCS data set.

Physician and practice characteristics, such as specialty, HMO owned practice and managed care contracts, all have significant effects on generic prescribing rates. However, after controlling for drugs prescribed, specialists and primary care physicians do not have different generic prescribing habits. This suggests that differences between primary care physicians and specialists in terms of generic prescribing habits (and adoption of generic drugs), on average, can be attributed entirely to the differences in drug case-mix for primary care physicians and specialists. The Health Tracking Physician Survey of 2008 showed strong evidence that physician's self-assessed generic prescribing habits are associated with compensation from the pharmaceutical and medical device industry. Physicians who admitted to benefits such as free food and compensation for travel to conferences were less likely to say they frequently prescribed generics. This effect was stronger the more total financial compensation the physician received. The rather pervasive nature of some forms of industry influence, such as free food, raises the question of when these sorts of compensations cross the medical profession's ethical boundaries and improperly affect patient care.

These findings give some leads on the incentives and characteristics that affect physician prescribing habits. Public health officials who want to promote generic drug usage may want to selectively target areas of concern, such as potential conflict of interests due to industry influence, practices with no managed care contracts and practices without electronic prescribing.

This may be accomplished through academic detailing programs, Medicare incentive programs, accelerated usage of the generic drug name and the publication of pharmaceutical industry compensation of physicians, among other programs.

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A Appendix: NAMCS

Data

The NAMCS data set includes up to eight drugs prescribed by the physician for each patient encounter. In order to address whether it will be appropriate to run the regression analysis on only the first encoded medication, an analysis of the generic prescribing rates for the eight drug mentions has been done, shown in Table A.1 below. Medicines that are continued, rather than a new prescription, are more likely to be prescribed as a generic, except for the first drug mention encoded.

Table A.1: Generic Prescribing Rates by Number of Patient's Medication

	Overall		**New**		**Continued**	
Medication	**Mean**	***N***	**Mean**	***N***	**Mean**	***N***
First	29.1%	87342	29.2%	30816	28.8%	54072
Second	31.7%	59752	30.8%	16757	32.1%	41774
Third	33.7%	42060	32.6%	9752	34.1%	31504
Fourth	34.7%	30601	32.9%	6280	35.2%	23719
Fifth	35.4%	22844	36.1%	4452	35.3%	17968
Sixth	36.3%	17132	36.8%	3260	36.2%	13566
Seventh	35.1%	12759	36.8%	2378	34.8%	10140
Eighth	34.7%	8965	36.3%	1745	34.3%	7055

Some variation in the generic prescribing rates is to be expected as the patients who have more than one drug mention are a subsection of the overall population and may have very specific characteristics (selection bias). As Table A.1 shows, however, there are large differences between the prescribing rates of the first drug prescribed and the ensuing drug mentions. These differences are highly statistically significant. This could be due to a selection issue - that patients who receive multiple medications are observably different than those that only receive a single prescription (e.g. age) or these patients they could be more cost-sensitive or familiar with the generic form of the drugs. Another possibility is that the order the drugs are encoded in the database are non-random and drugs that are less likely to be prescribed as generics are coded first by the physician. This finding could also be due to differences in the type of drugs that are typically prescribed in combination with other drugs and those that are typically the

only ones prescribed. To control for whether this finding is due to the drug "case-mix" (i.e. drugs that are more likely to be prescribed as generics are more likely to be prescribed in combination of other drugs), the same calculations are made with the top forty most popular drugs in the data set, shown in Table A.2. Again the same general pattern is found, where the first drug prescribed had a lower overall generic prescribing rate in comparison with the second through eight drug mentions.

Table A.2: Generic Prescribing Rates by Number of Patient's Medication, Top Forty Drugs

	Overall		**New**		**Continued**	
Medication	**Mean**	***N***	**Mean**	***N***	**Mean**	***N***
First	34.8%	35425	36.5%	11936	34.0%	22658
Second	37.8%	23026	36.3%	4448	38.2%	17895
Third	39.4%	16730	36.6%	1983	39.9%	14279
Fourth	40.5%	12305	39.4%	1031	40.7%	10906
Fifth	40.4%	9001	36.1%	623	40.9%	8067
Sixth	40.6%	6870	37.3%	434	40.9%	6225
Seventh	40.2%	4864	35.8%	282	40.5%	4426
Eighth	39.3%	3379	34.2%	228	39.7%	3026

To control for whether this could be due to systematic reporting biases by the physicians in encoding the drugs prescribed, a conditional probability analysis is performed for the generic prescribing rate among patients who received at least two drug prescriptions. Importantly, controlling for the generic prescribing rate for patients who received at least two top forty drug prescriptions, the generic prescribing rate is 38 to 39 percent (statistically insignificant). The conditional probability analysis (Table A.3) found no statistically significant differences between the encoding of the first and second drug mention among this subpopulation, suggesting that we do not have to be concerned about systematic reporting biases and that the differences in the generic prescribing rate between the first drug mention and the second drug mention found in Tables A.1 and A.2 are due to either drug "case-mix" differences or patient characteristics differences due entirely to the subgroup of encounters which have only one prescribed medication. These findings suggest that a regression analysis on generic prescribing habits using only the first drug mention can be appropriate; however, caution should be used in assessing the broader implications of the regression model, especially in the comparison of patients who are

prescribed only a single medication and those that are prescribed multiple medications.

Table A.3: Generic Prescribing Rate Among Patients with at Least Two Top Forty Drugs Prescribed

	X=1st, Y=2nd	**X=2nd, Y=1st**
Pr(Mention X = 1 | Mention Y)	0.3803	0.3895
Std. Error	(0.0051)	(0.0051)
N	9095	9095
Pr(Mention X = 1 | Mention Y = 1)	0.4358	0.4463
Std. Error	(0.0084)	(0.0085)
N	3543	3549
Pr(Mention X = 1 | Mention Y = 0)	0.3449	0.3546
Std. Error	(0.0064)	(0.0064)
N	5552	5636

Orange Book Data

The average generic prescribing rate, generic search popularity and monopoly duration length for the top 40 drugs in the data set are shown below in Table A.4.

Table A.4: Summary Statistics for Top 40 Drugs

Variable	**Mean**
Monopoly Duration	9.58
	(0.034)
Generic Search Popularity	0.42
	(0.002)
Generic Rx	0.32
	(0.003)
N	34,617

NOTE – Standard errors in parentheses.

The drug characteristics derived from the FDA Orange Book, such as whether the drug is an NTI, has an extended release formulation (XR), is multisource (MS) at some point between 2006-2010, approved before 1982 (P-1982) and brand-name and generic approval dates are shown in Table A.5, below.

Table A.5: Data From Orange Book for Top 40 Drugs

ID	Name	Works	NTI	XR[a]	MS[b]	P-1982	BN Approval	G. Approval
d00732	LISINOPRIL	1	0	0	1	0	12/29/87	05/19/88
d00088	AMOXICILLIN	3	0	0	1	1	01/01/82	01/01/82
d04105	ATORVASTATIN	2	0	1	0	0	12/17/96	11/30/11
d00749	ALBUTEROL	3	0	0	1	1	01/01/82	02/21/92
d00278	LEVOTHYROXINE	3	1	0	1	1	01/01/82	06/05/02
d00004	ATENOLOL	3	0	0	1	1	01/01/82	12/19/91
d04812	ESCITALOPRAM	2	0	0	0	0	08/14/02	09/11/12
d00022	WARFARIN	3	1	0	1	1	01/01/82	03/26/97
d00350	PREDNISONE	3	0	1	1	1	01/01/82	01/01/82
d00880	SERTRALINE	1	0	0	1	0	12/30/91	08/11/06
d00091	AZITHROMYCIN	1	0	0	1	0	08/19/96	11/14/05
d00089	A-C[c]	1	0	1	1	0	08/06/84	01/25/05
d00011	CIPROFLOXACIN	1	0	1	1	0	08/22/87	06/09/04
d03428	A-H[d]	3	0	0	1	1	01/01/82	10/23/02
d03807	METFORMIN	1	0	1	1	0	03/03/95	01/24/02
d00134	METOPROLOL	3	0	1	1	0	03/30/84	01/27/94
d00096	CEPHALEXIN	3	0	0	1	1	01/01/82	02/13/87
d04749	ESOMEPRAZOLE	2	0	1	0	0	02/20/01	
d04121	TAMSULOSIN	1	0	0	1	0	04/15/97	03/02/97
d00689	AMLODIPINE	1	0	0	1	0	07/31/92	10/03/05
d00253	HCTZ[e]	3	0	0	1	1	01/01/82	01/01/82
d00236	FLUOXETINE	1	0	1	1	0	12/29/87	08/02/01
d04258	CLOPIDOGREL	2	0	0	0	0	11/17/97	05/17/12
d00746	SIMVASTATIN	1	0	0	1	0	12/23/91	12/20/06
d03431	A-O[f]	3	0	0	1	0	11/23/01	06/30/04
d04113	VALSARTAN	2	0	0	0	0	07/18/01	09/21/12
d04109	LEVOFLOXACIN	2	0	0	0	0	12/20/96	06/20/11
d00070	FUROSEMIDE	3	0	0	1	1	01/01/82	11/30/83
d05355	DULOXETINE	2	0	0	0	0	08/03/04	06/11/13
d00168	ALPRAZOLAM	3	0	1	1	1	01/01/82	12/29/95
d04289	MONTELUKAST	2	0	0	0	0	02/20/98	08/03/12
d04115	TOPIRAMATE	1	0	0	1	0	12/24/96	04/17/09
d03182	GABAPENTIN	1	0	0	1	0	12/30/93	09/12/03
d04035	A-D[g]	2	0	1	0	0	10/11/01	10/21/18
d04380	CELECOXIB	2	0	0	0	0	12/31/98	11/30/13
d04223	MOMETASONE	2	0	0	0	0	10/01/97	01/27/14
d04611	F-S[h]	2	0	0	0	0	08/24/00	02/23/16
d00963	CBP[i]	3	0	1	1	1	01/01/82	11/27/91
d00181	BUPROPION	1	0	1	1	0	12/30/85	02/07/00
d04851	ROSUVASTATIN	2	0	0	0	0	08/12/03	08/04/20

NOTE – [a]Extended Release, [b]Multisource, [c]AMOXICILLIN-CLAVULANATE,
[d]ACETAMINOPHEN-HYDROCODONE, [e]HYDROCHLOROTHIAZIDE,
[f]ACETAMINOPHEN-OXYCODONE, [g]AMPHETAMINE-DEXTROAMPHETAMINE,
[h]FLUTICASONE-SALMETEROL, [i]CYCLOBENZAPRINE.
Works is 1 if there are no issues with the drug, 2 if the drug is not multisource, 3 if there are other issues with the drug (e.g. albuterol formulation has recently changed after the FDA banned the use of CFCs).

Summary Statistics for Important Independent Covariates

The nationally representative, survey-weighted means of the variables for the entire data set (N = 154,421) is given in the first column. The second column contains the same survey-weighted means of the variables for the encounters in which a multisource drug is prescribed by a physician (N = 68,951). The mean values for most of the variables do not change appreciably. The third column is the average generic prescribing rate (as a percentage) for the variable of interest.

Table A.6: Summary Statistics

	All Observations	Multisource Drug Prescribed		
Variable	**Mean**	**Mean**	**Mean GPR (%)**	**N**
Dependent Variable				
Generic Prescribed	–	0.3073	31.16	68,951
Time Effects				
Year	2008.05	2008.02	–	–
2006	–	–	24.48	13,521
2007	–	–	28.87	15,474
2008	–	–	30.68	12,442
2009	–	–	32.90	14,170
2010	–	–	39.31	13,344
Fixed Effects				
Northeast	0.1884	0.1860	30.15	13,507
Midwest	0.2101	0.2145	32.40	16,157
South	0.3920	0.3976	26.35	23,280
West	0.2095	0.2019	37.87	16,007
MSA	0.8791	0.8718	31.32	60,875
Poverty 0-5%	0.2237	0.2191	28.80	14,227
Poverty 5-9.99%	0.3099	0.3124	31.73	20,324
Poverty 10-19.99%	0.3164	0.3219	31.28	20,686
Poverty 20%+	0.1351	0.1325	32.35	9,631
Drug Characteristics				
Anti Infectives	0.0921	0.1824	30.35	11,133
Cardiovascular Agents	0.0911	0.1716	51.94	12,031
CNS Agents	0.1408	0.1905	19.62	14,282
Coagulation Mods	0.0112	0.0232	13.93	1,658
GI Agents	0.0313	0.0389	11.52	2,300
Hormones	0.0467	0.0740	35.96	4,747
Resp. Agents	0.0513	0.0543	48.65	3,400
Topical Agents	0.0622	0.0689	25.79	4,409
Psych Agents	0.0406	0.0842	20.72	7,172
Met. Agents	0.0524	0.0921	36.45	6,027
Antineoplast	0.0103	0.0172	23.95	1,503
Genitourinary	–	–	12.46	289
All Other/No Drug	0.3700	0.0000	–	–
Combination	0.1604	0.0918	5.62	6,049
Not Controlled Substance	0.8932	0.8897	32.98	61,222
Generic Name Longer	–	0.9044	26.76	62,428
Patient Characteristics				
Age	45.29	49.85	–	–
Male	0.4112	0.4191	32.32	29,559
Hispanic	0.1225	0.1092	35.77	7,989
Black	0.1101	0.1085	33.56	7,917
Other	0.0519	0.0438	37.38	3,604
Adverse Effects	0.0237	0.0197	28.89	1,253
No. of Meds Prescribed	2.3785	3.4478	–	–
Continued	–	0.5989	32.04	43,452
No Chronic Conditions	0.4393	0.3207	26.99	21,999
Patient was referred	0.1562	0.1389	31.01	12,326
Reason for Visit: Acute	0.3419	0.3618	32.60	22,340
Past Visits (0)	0.1980	0.1620	33.33	12,319
Past Visits (1-2)	0.3104	0.3034	31.30	21,035
Past Visits (3-5)	0.2712	0.2980	31.61	19,290
Past Visits (6+)	0.2204	0.2367	28.93	16,307
Payment Source				
Private Insurance	0.6355	0.6341	29.83	40,274
Medicare	0.2438	0.2888	31.87	19,791
Medicaid	0.1313	0.1184	32.62	9,626
Workers' Comp	0.0135	0.0098	18.94	602
Self Pay	0.0509	0.0525	31.39	4,880
No Charge	0.0046	0.0042	36.86	643
Other	0.0281	0.0262	35.17	2,431
Don't Know	0.0242	0.0223	39.94	1,790
Practice Characteristics				
Primary Care Physician	0.4582	0.5098	34.00	28,399
HMO Owns Practice	0.0206	0.0201	64.22	1,551
Solo Practice	0.3166	0.3159	27.00	20,404
No Managed Care Contract	0.7833	0.8083	30.11	53,003
Rev.: Medicare 50%+	0.1444	0.1679	29.66	10,650
Rev.: Medicaid 50%+	0.0600	0.0451	34.90	4,347
Rev.: Private Ins. 50%+	0.3532	0.3308	29.83	20,040
Rev.: Patient 50%+	0.0203	0.0184	27.25	2,136
Sample Size (N)	154,421	68,951		

Results

Generic Search Popularity, Examples

There is a strong correlation between the generic search popularity and the generic prescribing (Figure A.1). These six drugs are representative of different drug idiosyncratic prescribing. Lisonopril and amoxicillin are almost always prescribed as a generic. Atorvastatin is not a multisource drug (in this sample period). Albuterol has been widely prescribed as a generic, but is being prescribed as a drug less often, perhaps in response to changes in the product after the FDA phased out the use of CFCs as propelent at the end of 2008. This may have forced a reformulation of the drug delivery system, and reduced the quality of the generic alternatives. There is a sharp reduction in physician prescribing of generic albuterol corresponding to the end of 2008. Sertraline and azithromycin are both drugs that came of patent in 2006 and 2005 respectively, and show a rise in generic drug prescribing, corresponding to generic search popularity. However, physicians' generic prescriptions lag the dispensing of the drug as sertraline and azithromycin was predominantly dispensed in the generic form soon after the introduction of the generic.

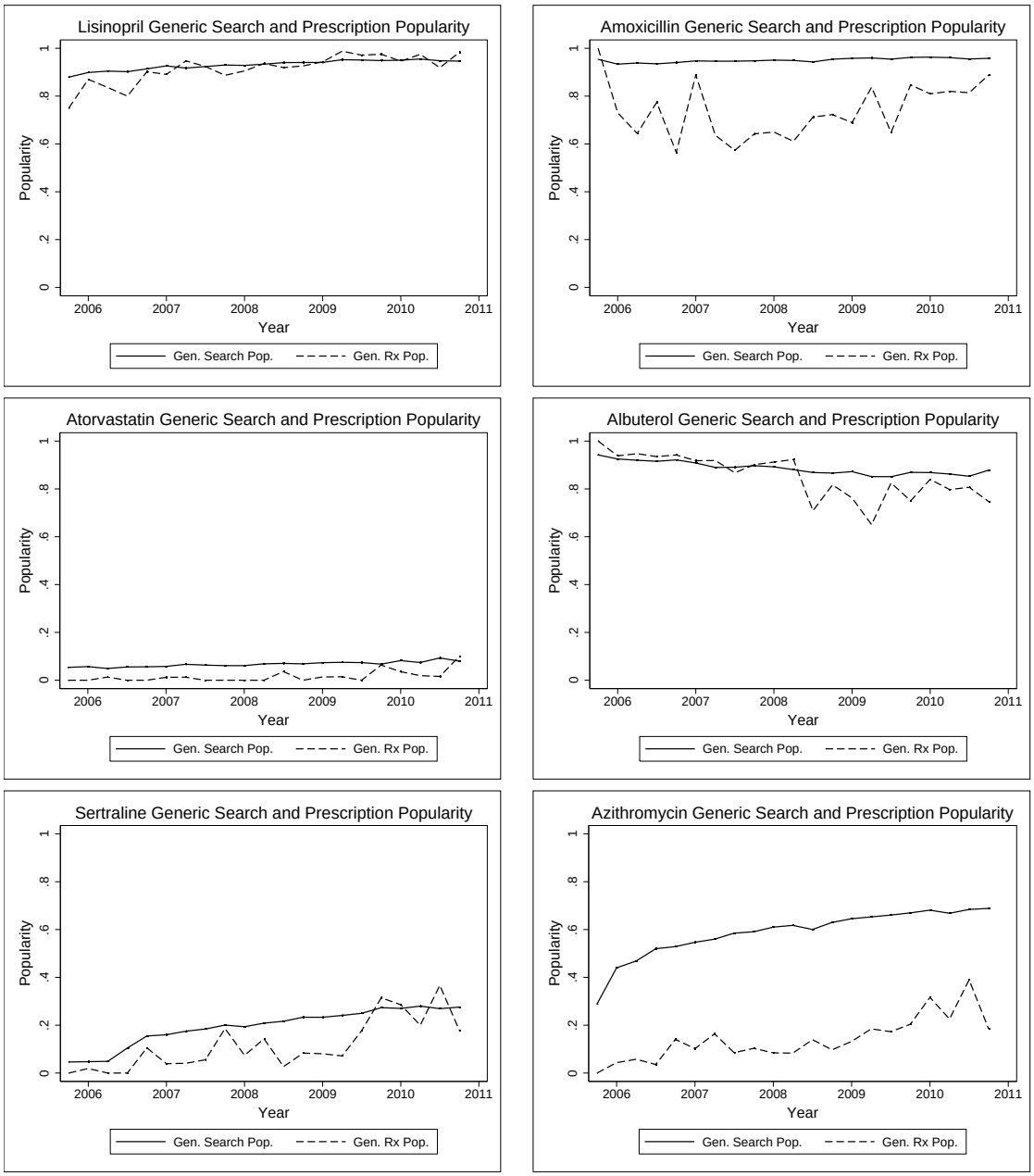

Figure A.1: Examples of Correlation Between Generic Search Popularity and Generic Prescribing, Quarterly Averages

PCP vs. Specialists Drug Case-Mix

The entirety of the differences in generic prescribing between primary care physicians and specialists can be attributed to the difference in the drug case-mix. Table A.7 shows the chi-square test of association for the primery care physician and specialist drug-mix, for each of the four drug classes.

Table A.7: Chi-square Test of Association for Drug Case-Mix, PCP Versus Specialist

	CVD	**Hormones**	**Psych Agents**	**CNS Agents**
Chi-Sq Test of Association	4.2×10^{-123}	5.0×10^{-162}	1.0×10^{-75}	0
Drugs (N)	56	26	31	91

B Appendix: HTPS

Data

The correlation matrix for the industry influences variables are shown in Table B.1, below.

Table B.1: Correlation Matrix for Industry Influence Variables

	FREEFD	FREERX	HNSPEAK	HNSRVY	PYCNSLT	CSTTRVL	CMECRDT	GFTOTHX	MRELCMPX
FREEFD	1.00								
FREERX	0.46	1.00							
HNSPEAK	0.16	0.12	1.00						
HNSRVY	0.18	0.18	0.23	1.00					
PYCNSLT	0.08	0.08	0.38	0.20	1.00				
CSTTRVL	0.11	0.07	0.35	0.17	0.33	1.00			
CMECRDT	0.08	0.09	0.03	0.13	0.06	0.14	1.00		
GFTOTHX	0.09	0.08	0.14	0.14	0.14	0.15	0.11	1.00	
MRELCMPX	0.23	0.19	0.62	0.42	0.45	0.40	0.12	0.19	1.00