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The importance of the physician in the generic versus trade-name prescription decision

Judith K. Hellerstein*

I examine the importance of physicians in the process by which patients receive either trade-name or generic drugs. Using a dataset on physicians, their patients, and the multisource drugs prescribed, I find that almost all physicians prescribe both types of drugs to their patients, but some physicians are more likely to prescribe generic drugs while other physicians are more likely to prescribe trade-name drugs. Very little of the prescription decision can be explained by observable characteristics of individual patients, but all of the evidence indicates that physicians are indeed an important agent in determining whether patients receive either trade-name or generic drugs.

1. Introduction

■ In 1989, over 70% of pharmaceutical prescriptions were written for multisource drugs, that is, drugs for which both generic and trade-name versions are available. Yet of these multisource prescriptions, fewer than 30% specified the generic version of the drug. Since generics are generally priced 30–60% lower than their trade-name counterparts (Grabowski and Vernon, 1992), substantial cost savings could be realized in this $40-billion-per-year market if generics captured greater market share. Possible explanations for the paucity of generic prescriptions include the existence of information imperfections that limit the physician's knowledge, and agency problems arising from the physician acting as agent for the patient and for the patient's insurance company.

In this article I examine whether the seemingly small market share of generics can be attributed at least partially to the behavior of physicians. Using data from a survey of physicians, their patients, and the drugs prescribed, I examine whether physicians vary their prescription decisions on a patient-by-patient basis or whether they systematically prescribe the same versions (trade name or generic) to all patients. I test whether

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physicians are more likely to prescribe generics to patients who do not have insurance coverage for prescription pharmaceuticals. I also examine the effects of state legislation on generic prescription.

The results indicate that physicians are indeed key decision-making agents in the prescription decision. The reason why some physicians are more likely to prescribe generic drugs while others are more likely to prescribe trade-name drugs is largely left unexplained. Studying the evolution of physician behavior and how it is affected both by mechanisms of information diffusion (such as advertising) and by the structure of the health care delivery system should be an important topic for future research.

The article proceeds as follows. Section 2 reviews the basic facts and existing literature involving generic pharmaceuticals, insurance coverage for prescription drugs, and other salient institutional facts. Section 3 describes the characteristics of the dataset used and reports relevant summary statistics. Section 4 introduces a model of physician demand for generics, and Section 5 discusses an empirical estimation framework based on this model and the data. Section 6 discusses the estimation results and their interpretation. Section 7 contains the conclusion and suggestions for future research.

2. Background and related literature

■ **The introduction of generics.** Before 1984, generic pharmaceuticals were relatively uncommon. Any firm that wanted to market a post-patent expiration generic had to prove to the Food and Drug Administration (FDA) the drug's efficacy and safety by conducting exactly the same tests as those required of the original innovator. This constituted a substantial barrier to entry.[1]

In 1984, Congress passed the Drug Price Competition and Patent Term Restoration Act of 1984, commonly known as the Waxman-Hatch Act. This legislation was intended to reduce expenditures on prescription drugs by encouraging generic entry. It eliminated the strict requirements for FDA approval of generic substitutes and replaced it with one that requires much less stringent testing.

The Waxman-Hatch Act stipulates that a firm wishing to gain approval for distribution of a generic drug must prove to the FDA that its drug is essentially the same as the original patented drug in all dimensions except inert ingredients, shape, packaging, labelling, and shelf life. Passage of the Waxman-Hatch Act was followed by a dramatic increase in the number of generic drugs in the market (Grabowski and Vernon, 1992).

□ **State substitution laws.** The other major legislative change affecting generic entry has been the repeal of state antisubstitution laws. Twenty-five years ago, most states had some kind of law that prohibited a pharmacist from dispensing any drug other than the one expressly written by the physician. This barred generic substitution by pharmacists. By 1989, in response to growing concerns about the perceived high costs of prescription drugs, all states had repealed these laws in an effort to encourage the use of generic drugs.

Most states now have what are known as "permissive substitution laws" that allow a pharmacist to substitute a therapeutically equivalent drug for the one written on the prescription.[2] Twelve states have mandatory substitution laws that require the pharmacist to substitute if the generic drug is in stock and is cheaper than the prescribed

[1] The only exception to the pre-1984 FDA approval process was for antibiotics. Approval to produce generic antibiotics has always been relatively easy. For more details, see Hellerstein (1995).

[2] For a detailed study of the effects of state legislation on pharmacist substitution in the early 1980s, see Masson and Steiner (1985).

drug.[3] In both cases, the physician can override the possibility of substitution by prohibiting pharmacist substitution on the prescription itself. I discuss below how these laws can affect physician behavior.

There are two methods of substitution prevention. In both methods, the physician must sign the prescription. The difference between the methods has to do with how the physician prohibits substitution by the pharmacist for generics. Some states use prescription pads with the "two-line method." In this method the physician signs the prescription either on a line that reads "brand medically necessary" or on a line that reads "substitution allowed." The line on which the physician signs his or her name thus determines whether the pharmacist can substitute.[4] Other states have a one-line method (also called "active substitution method"), in which the physician signs the prescription in only one place. If the physician just signs his or her name, the pharmacist is allowed to substitute and dispense a generic. In one-line states, to prohibit substitution the physician, in addition to signing the prescription, must take some extra action. This can take the form of entering the physician's initials in a box at the bottom of the prescription form or writing "brand medically necessary" in a designated spot on the prescription.

Interestingly, this seemingly minor difference in prescription pads (that is, the extra action in one-line states of putting initials in a box or writing three extra words) has a huge impact on whether substitution is allowed. In 1989, substitution was prohibited in 41% of two-line brand-written prescriptions but in only 11% of brand-written prescriptions that required more than a signature from the physician (*Drug Topics*, 1991).[5] This difference in prescription-writing behavior clearly shows that even very small costs have a large effect on physician decisions. Why this extra action matters so much is not clear, but given the small cost of adding extra information to the prescription, the difference in prescription-writing behavior across states suggests the presence of serious agency problems in the current delivery system for prescription drugs.

With all of this legislation to promote substitution, it is rather surprising that generic substitution by pharmacists is not very prevalent. Generic substitution by pharmacists occurred in less than 30% of trade-name-written prescriptions (for which a generic was available) in 1989, while nearly all prescriptions written by physicians for generics were, in fact, filled by pharmacists with the generic drug (Caves, Whinston, and Hurwitz, 1991). It seems that strict adherence to state legislation on the part of pharmacists is probably not occurring, although data on this are sketchy. Because generic substitution by pharmacists does not occur in the majority of the cases—either because of physician prohibition or pharmacist or patient preferences—the actual drug name written on the prescription by the physician still has the greatest impact on which type of drug the patient will receive. The decision to write the trade name or generic name on the prescription is exactly the decision studied in this article.

□ **Physician prescription practices: the roles of information imperfections, agency, and moral hazard.** The purpose of this section is to outline possible reasons why

[3] The states with mandatory substitution laws are Florida, Hawaii, Kentucky, Massachusetts, Mississippi, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, Washington, and West Virginia.

[4] The states with the two-line method are Alabama, Arizona, Idaho, Illinois, Indiana, Kansas, Mississippi, Missouri, North Carolina, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Vermont, Washington, and Wyoming. I code Maine as having a one-line substitution law since the law says that to prohibit pharmacist substitution, a physician in Maine must check a box on the prescription form. It appears that in *Drug Topics* (1991), Maine is categorized as a "two-line" state. Given how few prescriptions are written in Maine, into which category it is placed is not quantitatively important.

[5] The figures reported in *Drug Topics* (1991) are raw differences across states. No further breakdowns of the data on substitution patterns are given.

physicians do not prescribe generic drugs more often. In the empirical work that follows, I explicitly test for some of these reasons. Others (especially information imperfections) are not tested explicitly but are important and help motivate the empirical work.

Since physicians generally do not benefit financially from the prescription choices they make for their patients,[6] it might seem that physicians should act as perfect agents for their patients, prescribing only those drugs that the patient would choose if the patient were the decision-making agent (as suggested by Dranove (1989)). If, however, there are costs to the physician associated with prescribing drugs, physicians may not act as perfect agents for their patients.

These costs to the physician of prescribing drugs can take many possible forms, one of which, the small cost of filling out the information on the prescription pad, was discussed in the previous section. Another cost to the physician comes from collecting information on the availability and efficacy of generics and the price differential between generics and trade-name drugs. After the patent on a trade-name drug expires, it may take time for information to diffuse about the existence and name of the generic. In addition, a risk-averse physician may not prescribe a generic until its efficacy is well established. Generic drug manufacturers do very little advertising, while information about new trade-name drugs is widely disseminated formally through advertising and the published results of drug efficacy studies. It may therefore be much more costly to a physician to learn about the introduction of new generic drugs. In addition, there is evidence that physicians have little knowledge of actual drug prices (Temin, 1980; Kolassa, 1995). Despite large expenditures on advertising in the industry,[7] promotional information seldom reports actual prices.[8] The fact that physicians do not know the costs of the drugs they prescribe suggests that they cannot be fully price sensitive in that, at best, they can only estimate the magnitude of cost savings from generics.

In general, the existence of any positive costs (even if small) associated with information collection about generics may lead the physician to underinvest (relative to the patient's optimum) in gaining this information, since the physician gets essentially no direct return to the investment. Indeed, the whole issue of agency imperfections in physician decision making was one of the implicit motivations for the passage of state substitution laws that make it easier for pharmacists to substitute generic drugs when physicians write prescriptions for trade-name drugs. With these laws, the physician does not have to have any explicit information about the existence of a generic drug. The physician can write a prescription for a trade-name drug knowing that unless the prescription prohibits substitution by the pharmacist or unless the patient refuses, the patient will receive a generic version if one exists.

Even if the physician acts as a perfect agent for his or her patients, there may still be agency problems associated with prescription decisions if the physician is acting as perfect agent for the patient but not for the patient's insurer. This type of agency

[6] Only 2% of physicians dispense their own drugs (Shah, 1992), and the practice is outlawed in some states. This is not to say that physicians do not benefit from relationships with pharmaceutical companies. The direct advertising that pharmaceutical companies undertake, called "detailing," can lead to lucrative rewards for physicians. It is unlikely, however, that physicians perceive that these rewards result from the actual prescriptions they write.

[7] Caves, Whinston, and Hurwitz (1991) find that for their sample of drugs, average sales promotion as a proportion of sales was 6% in the year in which the patent expired.

[8] An interesting piece of evidence pointing to the lack of information on the part of physicians is the success of Medco, a large mail-order pharmacy, which contacts physicians to try to persuade them to substitute lower-priced drugs for the drugs they have prescribed. Medco persuades physicians to switch to the lower-cost product in one-quarter to one-half of the cases it pursues (Boston Consulting Group, 1993). This indicates a willingness of some physicians to be price-sensitive given adequate information on efficacy and price.

problem has been called "moral hazard" in the market for insurance. This use of the term "moral hazard" follows Pauly (1968) and the definition often used in the health economics literature. It refers to the fact that patients may demand (and receive) too much care relative to the social optimum because the existence of insurance means they do not directly bear the full marginal cost of care. This definition of moral hazard in insurance contrasts with the more commonly used definition, which suggests that the existence of health insurance leads patients to engage in more risky behavior. While this latter type of moral hazard certainly may exist, Pauly (1968) points out that even with totally risk-averse patients, the existence of insurance may lead to overconsumption of health care just because the marginal cost of treatment is not borne by the patient.[9] In the case of prescription drugs, moral hazard in insurance may mean that the insured patient does not have the incentive to induce the physician to invest in collecting information on low-cost treatments for patients with insurance. Even if the physician does have full information, moral hazard may mean that the patient does not demand the socially optimal amount of prescription drugs and instead receives either too many drugs or too expensive drugs (like trade names) relative to what is socially optimal. This type of suboptimal use of prescription drugs is modelled in the next section.

How insurance for prescription drugs affects physicians' prescription decisions depends in practice, of course, not only on the physician but also on the nature of the insurance. It is therefore important to understand the differences in the treatment of prescription drugs across different insurance plans in the United States.

There is wide heterogeneity across private insurance plans in the coverage of prescription pharmaceuticals. Figures from 1989 and 1990 indicate that 25–30% of private insurance plans had some prescription drug coverage.[10] Of those individuals covered by some prescription drug coverage, 3% had full coverage for prescription drugs, 30% had some copayment or separate deductible for prescription drugs, 61% had prescription drug coverage under the same rules as all coverage in their plan, and 7% were covered by other types of limits on payments (U.S. Congress, 1993). It is not clear how much physicians know about the prescription drug coverage of their patients with insurance, however, so it is not clear whether a physician treating a patient with private insurance will make prescription decisions based on the knowledge that the patient has insurance. I return to this point again in Sections 3 and 6 when discussing the data and empirical results.

Health maintenance organizations (HMOs), because of their distinct contractual structure in the delivery of health care, are a unique type of insurance provider for prescription drugs. In particular, HMOs, unlike traditional fee-for-service private insurance plans, often explicitly specify terms under which generic substitution by pharmacists is allowed. A 1988 survey of HMOs (Doering et al., 1988) found that over 70% of HMOs did have some sort of policy on generic substitution by the HMO pharmacy. Of the 188 HMOs that responded to the survey, 38.3% substituted generics except when prohibited by the physician and 32.5% dispensed generics except when the patient insisted on receiving the trade-name drug. In cases where the recipient refused the generic, the patient was usually required either to pay the price differential between the generic and the trade-name drug or to pay a higher copayment. In addition to these regulations on generic substitution by pharmacists, HMOs may alter physicians' prescription behavior by giving them more information about pharmaceutical options and by providing incentives to prescribe lower-cost drugs. This is discussed in more detail in Section 6.

[9] *This point was also made in passing by Arrow (1963).*

[10] The data on private insurance include the 14% of individuals covered by HMOs.

Although Medicaid recipients make up only 7% of the population, Medicaid accounts for 10–15% of total prescription drug sales (Boston Consulting Group, 1993) and approximately 50% of third-party payments for pharmaceutical products (Frank and Salkever, 1992). This is probably due to both a greater need for drugs by Medicaid patients and the fact that Medicaid has generous prescription drug coverage relative to other insurance plans. In 1989, Medicaid only required patients to pay, if anything, a very small copayment. In essence, Medicaid recipients received prescription drugs for free, making this population particularly interesting to study.

Medicare does not currently pay for any portion of prescription drugs, but a large fraction of Medicare recipients are also covered by other insurance plans. In 1987, for example, 10% of Medicare recipients were also covered by Medicaid, and a full 75% were covered by private insurance. Therefore, in most cases, a patient with Medicare has other insurance that may cover prescription drugs. So when a physician receives Medicare reimbursement for a patient visit, he or she may infer that the patient has private insurance that may cover prescription drugs.

The fact that there is such wide heterogeneity in the coverage of prescription drugs means that if there is moral hazard in insurance when it comes to physician prescription behavior, there will be differences in the propensity of physicians to prescribe low-cost generic drugs, and these differences will be (partially) a function of the insurance held by the patient. In particular, if moral hazard exists, patients with extensive insurance coverage for prescription drugs (like those on Medicaid in 1989) should receive prescriptions written for generic drugs less frequently than patients with no prescription drug coverage.

3. Empirical motivation and summary statistics

■ As described in Section 2, the forces determining the prescription choice of physicians are complex and numerous. Before outlining a formal model of the prescription choice or discussing an estimation strategy, it is useful to first consider relevant information from the dataset employed here, the 1989 National Ambulatory Medical Care Survey (NAMCS). Full details of the data and their construction appear in Appendix A. The full dataset consists of observations on 38,384 patient visits to 1,223 office-based physicians over the course of 1989. Physicians selected in the survey recorded information on a random sample of patients that visited their offices over a two-week period.

For each patient visit, the physician recorded the patient's demographic characteristics (age, sex, race, ethnicity) as well as information about his or her medical condition. No data on income or other similar characteristics of the patients are recorded. The physician recorded the names of up to five medications ordered. In the empirical analysis below, however, I examine data on only the first medication ordered by a physician for a patient because the sample sizes for other medications ordered were too small to be useful. It is important to understand that medications ordered were not necessarily the medications ultimately dispensed to the patient by the pharmacist. That is, the pharmacist could have substituted a generic version of the drug for a trade-name prescription. These data contain no information on what drug was ultimately dispensed to the patient. In addition, the data unfortunately do not indicate whether the physician prohibited substitution on the prescription pad. The data do, however, contain the state in which the physician practices, so it is possible to control roughly for the likelihood of substitution given the relevant state laws. As discussed in Section 2, state laws on the design of prescription pads are a large determinant of whether the physician prohibits substitution. Finally, the physician was asked to record the expected source(s) of

payment for the visit: self-pay, Medicare, Medicaid, Blue Cross/Blue Shield, other commercial insurance, HMO/prepaid plans, no charge, or other.

Table 1 contains summary statistics for the overall sample of patients. The most striking thing to note is that 27% of the sample is classified as being self-insured, which is a much higher figure than reported elsewhere. This discrepancy is most likely due to miscoding in the NAMCS data of insurance payments. Physicians in the survey were instructed to record a third-party payer as the source of payment if the patient paid at the time of the visit but was to be reimbursed later, but it is likely that physicians recorded some of these patients as paying for the visit themselves. The relevant information for the prescription decision, however, is the physician's perception of whether the patient has insurance. If this is, in fact, what the physician recorded in the data, then the insurance data are accurate for the problem at hand.

Over 90% of physicians in the NAMCS prescribed a multisource drug to at least one patient. These drugs can be divided into 20 therapeutic classes. Some of these classes contain very few observations and little variation in generic prescription decisions, so that within a class, physicians either always (or almost always) prescribe generics or always (or almost always) prescribe trade-name drugs. For the remainder of the article, I therefore concentrate only on prescription data from the eight largest therapeutic drug classes.[11] This has no qualitative effect on any results and causes only one physician to drop out of the sample. Summary statistics for this subset of patients are given in Table 2. Over the sample of patients, 29% of those receiving multisource drugs were prescribed the generic version of the drug.[12] Of particular note in Table 2 are the findings that (unconditionally) there are regional differences in generic prescription propensities (so that, for example, patients in the South are more likely to be prescribed trade-name drugs), and that patients belonging to HMOs and other prepaid plans are more likely to receive generic prescriptions.

Table 3 reports the frequency of generic prescription by drug class for the eight largest drug classes in the data. The sample consists of 492 uniquely named multisource prescription drugs, corresponding to 149 different generic compounds for which both trade-name and generic versions were available in 1989. There is a lot of heterogeneity across therapeutic drug classes in the frequency of generic prescription. For the largest drug class represented in the data, antimicrobials, 41% of the prescriptions are written for the generic, while in other drug classes generic prescription seldom occurs. Most antimicrobials are antibiotics, which have a longer history of generic entry than other drugs, and the names of the generics (e.g., penicillin, amoxicillin) are well known. In addition, although not completely consistent across drug classes, it appears that generic penetration is more prevalent for the more commonly prescribed drugs such as antimicrobials, cardiovascular-renals, and central nervous system drugs.[13] This fact is not surprising given that there are relatively large fixed costs associated with entry into a given generic market, particularly the cost of obtaining FDA approval.[14]

[11] If there is no variation in generic prescription rates within a given therapeutic class (so that either only generics are prescribed or only trade-name drugs are prescribed), observations for this therapeutic class contribute no information in the empirical analysis to help in determining what physician and patient-specific factors determine prescription decisions. This is because in the empirical work I condition on therapeutic class.

[12] The term "generic" is used rather loosely in many discussions of prescription pharmaceuticals. It can variously refer to versions of a drug sold under the actual generic name, or to drugs not marketed by the original innovator of the drug. In this analysis I use the former definition. Drugs classified as generics are those for which the physician recorded the name of the generic entity in the survey (and presumably on the prescription pad as well). Trade-name drugs refer to any drugs prescribed under a name other than the generic.

[13] This pattern is more apparent when generic rates from all eighteen drug classes are compared.

[14] In this article I focus on the importance of the physician in the prescription outcome, although the differences across drugs, as seen in Table 3, persist throughout the empirical work I present and are interesting in their own right.

TABLE 1 Summary Statistics for Overall NAMCS Patient Sample

Variable	Mean	Standard Deviation
Age	42.39	24.99
Female	.60	.49
Nonwhite	.11	.31
Hispanic	.05	.22
Self-pay	.27	.45
Medicare	.14	.35
Medicaid	.08	.26
Blue Cross/Blue Shield	.13	.33
Other commerical insurer	.24	.43
HMO/prepaid plan	.14	.35
Specialist	.55	.50
Northeast	.19	.39
Midwest	.26	.44
South	.34	.47
West	.21	.41

Notes: The sample size is 32,796. This includes only those observations for which valid data for each variable were available. Medicare patients are those for whom the physician recorded the patient visit as being paid for solely by Medicare. Patients who were not charged by the physician for the visit are excluded. Specialists are physicians who are not in general practice, family practice, or basic pediatrics.

This dataset is unusual because it links together patient-observations of a given physician. With this information it is possible to consider differences across physicians in their propensity to prescribe generics. Figure 1 graphs the smoothed distribution of generic prescription rates for the physicians in the survey. On the one hand, the figure makes it clear that physicians cannot be classified simply as "high-cost" or "low-cost," as most physicians tend to prescribe generics to some patients but not others. On the other hand, the relative smoothness of the distribution in the figure makes it clear that some physicians are more likely to prescribe generics while others are more likely to prescribe trade-name drugs.

To understand what is driving Figure 1, one would ideally like to observe a physician repeatedly prescribe the same type of drug to many patients (or even better, one drug to the same patient many times). This would determine conclusively whether the pattern seen in the figure is driven by differences in prescriptions across patients for a given drug or whether differences in generic or trade-name prescriptions are predominantly seen across drugs. Unfortunately, for a given drug, it is unusual to find a physician prescribe it to more than one patient in the sample, given that the sample size per physician is relatively small. On average, the data contain nine observations per physician of patients receiving multisource drugs.

It is possible, however, to conduct this type of analysis informally for a small subset of frequently prescribed drugs. In constructing Figure 2, I consider the subsample

TABLE 2 Summary Statistics for Patients in NAMCS Drug Sample

Variable	Mean	Standard Deviation	Proportion Generic
Age	41.07	26.23	—
Female	.59	.49	.28
Nonwhite	.11	.32	.32
Hispanic	.06	.24	.31
Self-pay	.31	.46	.30
Medicare	.15	.36	.23
Medicaid	.09	.29	.31
Blue Cross/other private	.32	.47	.27
HMO/prepaid plan	.13	.34	.34
Specialist	.43	.49	.26
Northeast	.17	.38	.31
Midwest	.28	.45	.28
South	.35	.48	.25
West	.19	.39	.33
Full sample			.29

The sample size is 8,579. This includes the subsample of patients from Table 1 who received a multisource drug from one of eight large drug classes (see Table 3 for list). The last column reports the proportion of generic prescriptions (versus trade-name prescriptions) in each category.

of physicians who (among other things) are observed to prescribe a drug in its trade-name or generic form to at least six patients.[15] This situation occurs 158 times in the data. I then calculate, for each of these 158 cases, how many times the physician prescribes the trade-name version of the drug and how many times the generic version of the drug. I then tabulate the results of this exercise for all 158 cases and report the results in Figure 2. For example, there is a physician in the data who prescribes the drug with the chemical name "cephalexin sodium" to six different patients in either its trade-name form or its generic form. The physician writes a prescription for "Keftab" (the trade-name version) to one patient and writes a prescription for "Cephalexin" (the generic version) to five patients. This physician is counted as one of the cases in the middle bar of Figure 2, the bar labelled "both versions," since the physician does vary his or her prescription decision (trade name or generic) for cephalexin sodium across the six patients.

In over 60% (93) of the 158 cases used to construct Figure 2, the physician always prescribes the trade-name version of the drug. This does not mean that these 93 physicians always prefer trade-name drugs. In fact, more than three-quarters of these physicians do prescribe generic forms of some other drug to other patients. Moreover, these 93 physicians are often observed to prescribe generics of another drug even *within* the same therapeutic class as the drug that is used in constructing Figure 2. Similarly, in

[15] The cutoff of six patients was made in order to best deal with the tradeoff between the number of physicians used in Figure 2 and allowing for the possibility of variability in generic versus trade-name prescription patients who are prescribed the same drug by a physician. Varying the cutoffs somewhat does not change the basic message of Figure 2.

TABLE 3 Frequency of Generic Prescription by Drug Class

Name of Class	Observations	% Generics
All Drugs	8,579	28.51
By drug class		
Antimicrobials	3,495	40.54
Cardiovascular-renals	1,275	20.63
Central nervous system	681	28.34
Hormones/hormonal mechanisms	927	39.27
Skin/mucous membranes	561	5.70
Ophthalmics	415	12.05
Pain relief	793	12.74
Respiratory tract	432	6.02

26% (43) of the 158 unique drug-physician matches that make up Figure 2, the physician always prescribes the generic version of the drug, yet almost all of these 43 physicians prescribe other trade-name drugs to other patients, even trade-name drugs within the same therapeutic class.

It is also worth noting that the drugs prescribed by physicians in the "only trade names" subset in Figure 2 are prescribed in their generic form by other physicians, and the drugs represented in the "only generics" subset are prescribed in their trade-name form by others as well. Therefore, Figure 2 is not a reflection of patterns that can be explained by which drugs these 158 physicians prescribe.

What Figures 1 and 2 together suggest is that physicians do vary their prescription decisions across patients. Nonetheless, these figures both suggest that there is some physician-specific component at work in the prescription decision, so that some physicians are more likely to prescribe trade-name drugs and some are more likely to prescribe generics.

The rest of the article is devoted to formalizing and trying to explain the patterns described in this section. I examine whether and how much a physician's decision to

FIGURE 1

DISTRIBUTION OF PHYSICIAN GENERIC PRESCRIPTION RATES

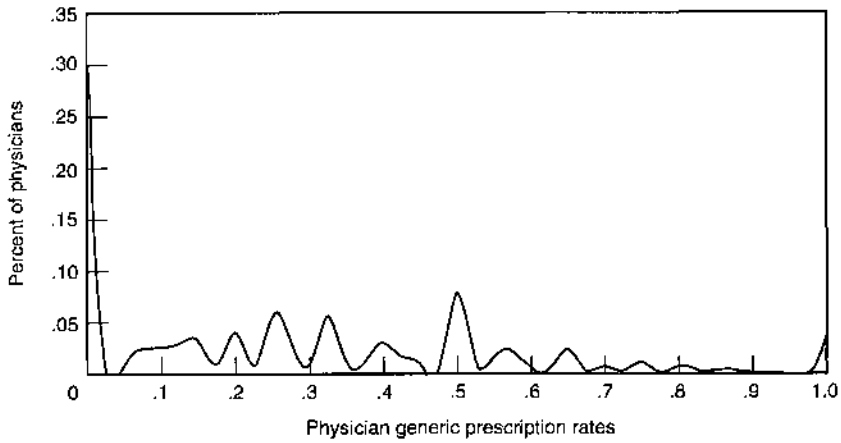
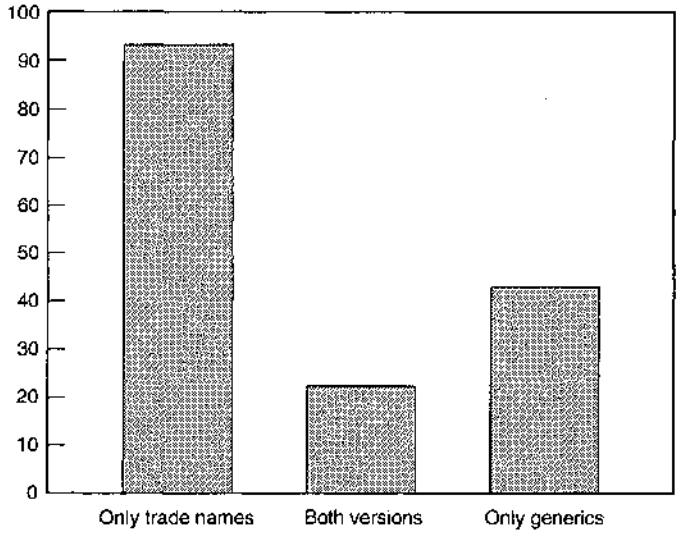


FIGURE 2

PHYSICIAN DECISIONS FOR PHYSICIANS WHO PRESCRIBE A DRUG TO AT LEAST SIX PATIENTS



prescribe generic drugs is a function of observable characteristics of the physician, the physician's patients, and the pecuniary incentives provided by state substitution laws.

4. The model

■ The purpose of developing a model of physician prescription behavior here is to parsimoniously fix the main issues involved with information imperfections and agency problems (including moral hazard) embodied in the prescription decision. The model must be applicable to a regression framework flexible enough to incorporate the constraints of the NAMCS data. Therefore, although prices are explicitly incorporated into the model, it should be noted that this is done for exposition only. In the ensuing empirical analysis, price data are not included; drug class dummy variables are instead used as proxies for price, and the implications of this are discussed.

First, consider a world without insurance. A price-taking patient i consumes a beneficial drug. The drug comes in either a trade-name version or a generic version, where the price differential between the two is ΔP. In states with mandatory substitution and full cost pass-through to consumers, the effective price of either version of the drug is the same, so ΔP will equal zero. However, in order not to complicate the basic model unnecessarily with issues of pharmacist substitution and varying state laws, assume for now that any trade-name prescription prohibits substitution. Define an indicator function G where $G = 1$ if the generic is prescribed and $G = 0$ if the trade-name is prescribed.

The physician j is the agent who writes down the name of the form of the drug (generic or trade name) being prescribed. As such, I define the utility function of the physician U_j in terms of the utility *differential* between prescribing the generic and prescribing the branded version of the drug:

$$U_j(G_i = 1) = [\gamma_i u_i(G = 1) - c_j], \tag{1}$$

where $0 \leq \gamma_i \leq 1$. The part of the utility function u_i is the utility to the patient from being prescribed the generic versus the trade-name version of the drug. The parameter

γ_1 is the proportion of the patient's utility that is internalized by the physician. If $\gamma_1 = 1$, the physician internalizes the full utility differential to the patient. If $\gamma_1 = 0$, the physician does not care about the patient's preferences at all. The physician may internalize a proportion of the patient's utility because of direct pecuniary incentives to do so (for example, the fear of losing the patient to another physician), or because of altruistic considerations.

The term c_j can be positive or negative and is the direct cost (or benefit) to the physician from prescribing the generic drug that arises separately from costs or benefits to the patient. In the context of heterogeneity across physicians at a point in time, c_j just captures differences across physicians in how likely they are to prescribe generics, conditional on the preferences of their patients. Testing for exactly how these differences arise is beyond the scope of this article, but they may arise both because of the physician's underlying propensity (preferences) for prescribing generics and because of the physician's actual past experience in prescribing generics.

Differences in both the propensity of physicians to prescribe generics and in physicians' experiences may arise because of differences in the institutional features of where physicians practice (urban versus rural, group versus single practice, etc.) or because of the demographic characteristics of physicians (age, place of medical education, etc.) or characteristics of their patients. Some physicians may be risk-averse people, in which case c_j would be greater than zero and could be thought of as a risk-aversion parameter that varies across physicians. Some physicians may have been trained to prescribe the generic version of a drug, while others may have been trained when the drug was still on-patent and therefore have a propensity for prescribing the trade-name drug. Some physicians may work largely in the prepaid-insurance world of HMOs, where cost containment is encouraged and where information about generics may be easier to obtain. In this case, c_j may be negative, so the cost of prescribing a trade-name drug would be high. Clearly, any of these differences in physicians' propensities for prescribing generics or experiences with generics could vary across drugs.[16]

One can therefore think of c_j in the context of the decision to prescribe a generic at a point in time as the adjustment "cost" required to break from previous behavior. This cost may be a direct economic cost, such as collecting new information about generics or having to place a telephone call to get a decision approved by a managed care administrator, or it may reflect the psychological cost of changing one's preferences. Unfortunately, because the NAMCS data were collected over too short a time, it is impossible using these data to study how behavior evolves and changes. Rather, the NAMCS data are most appropriately thought of as grouped data, where a group of observations without a time component are seen for each physician. One other shortcoming of the NAMCS data is that there is limited information on the background of the physician. For example, the data contain no information on the age, sex, race, or ethnicity of the physician, nor do they contain information on the physician's income or where the physician went to medical school. So in the empirical work, while I do account for differences in physician characteristics where the data permit, I am limited in my ability to account for all of the heterogeneity across physicians. Indeed, the empirical results indicate that most of the heterogeneity parameter c_j is left unexplained.

The utility function of the physician includes a term for the utility of the patient, $u_i(G = 1)$. The utility to the patient from being prescribed the generic is a function of the price differential between the generic and the trade name, and a function of any

[16] Heckman (1981a) provides one econometric formalization of how behavior evolves. Other behavioral models that might be applicable to physician decisions include rational addiction models (e.g., Baumgardner, 1994) and inductive-behavior and bounded-rationality models (Arthur, 1991). The key feature of all of these models is that multiple decisions made by an individual are likely to be nonindependent.

quality difference between the two forms. Define the (monetized) quality differential as q^*, so that the quality-adjusted price differential between the generic and the trade-name drug is $(\Delta P - q^*)$, where $q^* \geq 0$ (the trade-name drug is assumed to be of equal or better quality).

Different preferences among individuals (for example, due to differences in risk aversion) or nonhomothetic preferences among otherwise identical individuals with different incomes may lead to different optimal decisions about which form of the drug to consume. In addition, the quality differential between the two forms of the drug may differ across individuals based on sensitivity to inert ingredients, coloring, or other differences between the forms. If these differences in the utility function take the (not particularly restrictive) form of an additive term c_i to the adjusted price differential of the generic, we can say that a physician will prescribe the generic ($G = 1$) if

$$\gamma_1(\Delta P - q^* - c_i) - c_j > 0. \tag{2}$$

In other words, the physician prescribes the generic if the cost to the physician of prescribing the generic (c_j) does not outweigh the internalized portion of the patient's utility gain from paying for and consuming the generic. In Dranove's (1989) notion of agency on the part of the physician, the physician would be acting as a perfect agent for the patient if $\gamma_1 = 1$ and $c_j = 0$.

Now assume that the patient has insurance that covers a proportion θ of the cost of the drug, where $0 \leq \theta \leq 1$. If the physician acts as partial or perfect agent for the patient, but does not internalize any of the cost borne by the insurer, then the physician will prescribe the generic if

$$\gamma_1(\Delta P(1 - \theta) - q^* - c_i) - c_j > 0. \tag{3}$$

If insurance covers the full cost of prescriptions so that $\theta = 1$, or if there is no price differential between the generic and trade-name versions, then the physician will prescribe the generic if the cost c_j to the physician of prescribing the generic does not outweigh the benefit to the physician from prescribing the generic that arises when the physician internalizes some or all of the patient's benefits.[17]

The physician may internalize some or all of the cost of the drug to the insurance company. This may happen because the physician has a direct financial incentive to internalize this cost (for example, in the case of certain managed-care arrangements) or simply because the physician internalizes some or all of the social costs of health care expenditures, including those costs borne by insurers. Assume the physician internalizes a proportion γ_2 of the cost of the drug to the insurer, where $0 \leq \gamma_2 \leq 1$. Then (3) becomes

$$\Delta P(\gamma_1 - (\gamma_1 - \gamma_2)\theta) - \gamma_1(q^* + c_i) - c_j > 0. \tag{4}$$

If $\gamma_2 = \gamma_1$, we are back to the case in (3) because the physician does not distinguish between who is paying for the drug; the physician internalizes the same proportion of the price of the drug, regardless of whether or not the patient has insurance. In contrast, if $\gamma_2 < \gamma_1$, there is "moral hazard in insurance"; the physician is more likely to prescribe the trade-name drug if the patient has insurance, and this is an increasing function of the difference between γ_1 and γ_2.

[17] Additionally, if the insurance plan requires the patient to pay a fixed co-payment on all prescriptions, θ is effectively equal to one, since the insurer pays for the entire price differential between the trade-name and generic drug.

Consider expanding the model to an economy of J physicians and K drugs. Each physician j sees $I(j)$ patients. For ease of notation, let $I_j = I(j)$, and let i_j denote a patient of physician j.

The quality differential between the generic and trade-name version, q_k, is now drug-specific, as is the price differential, ΔP_k. In theory, there is reason to think that the parameters c_j and c_i might also have a drug-specific component. Given that in the NAMCS data a physician is only rarely observed to prescribe the same drug to multiple patients, and given that I only observe a patient once, I do not formally consider this possibility. Therefore, the jth physician will prescribe the kth drug in its generic form to the ith patient only if

$$\Delta P_k(\gamma_1 - (\gamma_1 - \gamma_2\theta_{i_j})) - \gamma_1(q_k^* + c_{i_j}) - c_j > 0. \tag{5}$$

Rearranging (5) to group subscripts, the physician prescribes the generic if

$$(\gamma_1\Delta P_k - q_k^*) + (\gamma_1 - \gamma_2)\theta_{i_j}\Delta P_k - \gamma_1 c_{i_j} - c_j > 0. \tag{6}$$

5. Empirical implementation

■ This section outlines the empirical strategy for estimating the impact of some of the physician- and patient-specific factors discussed in Section 4 on a physician's decision of whether or not to prescribe the generic form of a drug. For physician j, the NAMCS data can be described as

$$(G_{1_j}, \ldots, G_{I_j}, X_{1_j}, \ldots, X_{I_j}, P_{1_j}, \ldots, P_{I_j}, \tilde{X}_j, \tilde{P}_j, Y_j), \tag{7}$$

where G_{i_j} denotes whether or not patient i_j, who was prescribed a multisource drug, received the generic or trade-name version; X_{i_j} is a vector of personal characteristics of i_j (age, sex, race, and ethnicity);[18] P_{i_j} is a variable for what type of insurance the patient has; $\tilde{X}_j$ is a vector of characteristics of all other patients of physician j who did not receive a multisource drug; $\tilde{P}_j$ is a vector of insurance characteristics of those patients of physician j who did not receive a multisource drug; and Y_j is a vector of physician-specific characteristics including the physician's specialty and the state in which the physician practices.

Given this, I parameterize "$-c_{i_j}$" the patient-specific term in (6), as

$$-c_{i_j} = \beta X_{i_j} + \epsilon_{i_j}, \tag{8}$$

where ϵ_{i_j} is unobserved. Since I only observe one prescription per patient, ϵ_{i_j} may be partially a function of which drug is being prescribed, but it may also be due to any other randomness or characteristics of the patient that are unobservable. The insurance data are not included since, according to (6), insurance interacts with price.

The next thing to note is that the model as specified to this point includes prices, but the NAMCS data do not. Furthermore, the model assumes not only that the physician is explicitly price sensitive, but also that the physician knows the true price differential between the trade-name and generic version of the drug being prescribed. To the extent that the physician does not know true prices of the drugs, ΔP_k is more

[18] In this article I do not consider medical condition as part of the patient's relevant personal characteristics. The patient's condition obviously affects the type of drug prescribed, although this is probably no more than a small part of the particular decision of trade-name versus generic. The condition of the patient can be thought of as one of the unobserved characteristics of the patient that remains in the residual.

accurately defined as the physician's expectation of the price differential. This is obviously impossible to measure.[19] Instead, the linear drug term ($\gamma_1 \Delta P_k - q_k^*$) and the price term ΔP_k that interacts with the insurance term θ_{ij} are replaced with drug-class dummy variables, where the relevant drug classes are listed in Table 3. Drug-class dummy variables, rather than dummy variables for each unique drug, are used to reduce the dimensionality of the drug data. This is done for computational reasons, as explained below, and its implications are addressed in the empirical work.

The variable θ_{ij}, the proportion of drug costs covered by insurance, is also not known in the NAMCS data, although the type of insurance carrier the patient has is known. I therefore replace θ_{ij} by a vector of dummy variables indicating the patient's insurance type. Individuals for whom the physician recorded the visit as not being covered by insurance, so that $\theta = 0$, are left as the omitted group. If physicians act as agents for their patients but not for insurers so that there is moral hazard in insurance, the resulting coefficients on the insurance dummy variables should be negative. In addition, when estimating the model, patients who are covered by Blue Cross/Blue Shield or another commercial insurer are aggregated into one insurance group, and the small number of patients whose insurance is specified as "other" or as "no charge" are excluded.

I do not use physician-specific fixed effects to proxy for the term c_j. Unless the number of patients per physician is large, so that the data can be approximated with asymptotics where $I_j \to \infty$, estimates of the physician-specific fixed effects will be inconsistent.[20] More important, as Andersen (1973) shows, this inconsistency will be transmitted to the other parameters if the model is nonlinear. Given that this is a discrete choice (nonlinear) model, and given that the number of patients per physician who receive a multisource drug averages only 9, I treat the physician-specific effect as a nuisance parameter. It is for this same reason that I do not incorporate fixed drug dummy variables into estimation but rather incorporate solely drug-*class* dummy variables, where the number of drugs per class is relatively large and where I can be reasonably confident of estimating consistent drug-specific effects.[21]

I model the physician-specific nuisance parameter "$-c_j$" in the spirit of Mundlak (1978) and Chamberlain (1980). I assume that this term has a specific functional form:

$$-c_j = S_j \cdot \pi_1 + M_j \cdot \pi_2 + T_j \cdot \pi_3 + R_j \cdot \pi_4 + \overline{X}_j \pi_5 + \overline{P}_j \pi_6 + \nu_j. \tag{9}$$

The variables S, M, T, and R in (9) are dummy variables that represent the characteristics of the physician observed in the NAMCS. S is a dummy representing whether the physician is a specialist,[22] M and T indicate whether the physician practices in a

[19] Average list price is a reasonable candidate for a proxy for the expected differential, but even this may not be a good measure of price, since there is a lot of price discrimination in this market based on factors such as type of insurer and type of pharmacy. Incorporating price data into the estimation is therefore left for future research, but it is worth nothing that doing so is complicated by the fact that although it may be appropriate to treat physicians as price takers, prices are still not exogenous in an econometric sense. This is made precise in Kennan (1989).

[20] Another way to think about this is that the asymptotics under which fixed effects will be consistent are such that the number of observations grows at a rate faster than the number of parameters to be estimated. Given that the number of parameters grows with the number of physicians because of the fixed effects, this requires the number of patients per physician to grow at a rate faster than the number of physicians.

[21] Heckman (1981b) reports Monte Carlo results of the inconsistency of parameter estimates resulting from a fixed-effect probit model. He finds that for $I_j \geq 8$, the bias from the fixed-effect probit is small. Estimation results from a fixed-effect probit for the patient-specific coefficients on the subsample of physicians who treat eight or more patients are not qualitatively different from those reported below, which are derived from random-effect probit estimation. These results are available upon request.

[22] I define a specialist as a physician who is not a primary-care physician. That is, a specialist here is a physician who is not in general practice, family practice, or basic pediatrics.

state with mandatory substitution and two-line prescription pads, respectively, and R is a vector of regional dummies (Northeast, South, West, Midwest). The term ν_j is the remaining unobservable portion of the physician term. The incorporation of M and T linearly in the physician effect assumes that if the existence of state legislation promoting generic substitution by pharmacists affects the prescribing habits of physicians, it does so equally across all drugs. For instance, one could interpret an estimated negative coefficient on M as implying that physicians in states with mandatory substitution laws invest less in gaining knowledge about all generics and are therefore less likely to write the generic name on a prescription. As explained in Section 2, knowing the type of prescription pad the physician uses may be important because the prescription pad design affects the physician's probability of forbidding substitution, which may in turn affect the physician's probability of writing the generic or trade-name form of the drug on the prescription.

The parameters $\overline{X}_j$ and $\overline{P}_j$ are (row) vectors containing the average characteristics of the physician's patients. That is, $\overline{X}_j$ has as its elements the average age of the physician's patients, the percentage of females, the percentage of nonwhites, and the percentage of Hispanics, while P_j is a vector containing the percentage of physician j's patients in each insurance category. These averages include all patients in the NAMCS, including those who were not prescribed any drugs. (Recall that the age, sex, race, and ethnicity of each patient are also included as individual covariates in (8).) The average characteristics vector $\overline{X}_j$ is a proxy for unobserved characteristics of the physician that may affect prescribing habits and may be correlated with the characteristics of individual patients. For example, if a physician treats many elderly patients, he or she may be predisposed (via either propensity or past experience) to prescribing trade-name drugs, since small differences between generics and trade-name drugs may be important for elderly patients. This predisposition translates into a high adjustment cost c_j to the physician of switching to a generic, regardless of the actual age of the patient being treated. Alternatively, an older physician may be less likely to switch to a generic, having prescribed the trade name for many years. To the extent that older physicians tend to treat older patients, this will be captured in the average patient age component of $\overline{X}_j$ and will not bias the estimated coefficient on the individual patient's age.

Given this parameterization of the model, and given the fact that there are two random unobservables, (6) can now be rewritten in a probabilistic setting where the probability that the jth physician prescribes the generic form of the kth drug to the ith patient is

$$\begin{aligned}\text{Prob}[G_{ij} = 1 \,|\, C_k, X_i, P_i, S_j, M_j, T_j, R_j, \overline{X}_j, \overline{P}_j] \\ = \text{Prob}[C_k\lambda + X_i\beta + C_k \cdot P_i\gamma + S_j \cdot \pi_1 + M_j \cdot \pi_2 + T_j \cdot \pi_3 + R_j \cdot \pi_4 + \overline{X}_j \cdot \pi_5 \\ + \overline{P}_j \cdot \pi_6 + \nu_j + \epsilon_{ij} > 0],\end{aligned} \tag{10}$$

where C is a vector containing eight drug class dummy variables; X is a vector of the age of the patient, dummy variables for the sex, race, and ethnicity of the patient; P is a vector of four insurance dummy variables; and S, M, T, R, $\overline{X}$, and $\overline{P}$ are the elements of the physician-specific effect defined above.

I assume that the random terms ν_j and ϵ_{ij} are independent and distributed as $N(\mu_\nu, \sigma_\nu^2)$ and $N(\mu_\epsilon, \sigma_\epsilon^2)$, respectively. Without loss of generalization, the unobservable term $(\nu_j + \epsilon_{ij})$ can be normalized to be distributed $N(0, 1)$. Although the model then appears to be that of a simple probit, the correlation across patients of a given physician generated by ν_j renders probit estimation incorrect. To account for this, one could treat the usual probit likelihood function as a pseudo-likelihood function (as in Chamberlain

(1984)), where consistent estimates of the coefficients of the model can be obtained by maximizing the probit likelihood function, and standard errors can then be corrected to account for the correlation across patients.

A more efficient estimation strategy, the one used below, is to estimate a random effects probit specification by employing Gaussian Quadrature. This method explicitly accounts for the unobserved correlation across patients of a physician by estimating the parameter ρ, the proportion of the variance in the prescription choice that is physician- (but *not* patient-) specific. (Formally, $\rho = \sigma_v^2/(\sigma_p^2 + \sigma_z^2)$.) In contrast, there is no straightforward way to recover an estimate of ρ by maximizing the usual simple probit likelihood function, since its nonlinearity precludes a simple errors-in-components decomposition. Obtaining an estimate of ρ is important, as it gives some indication of what factors (physician- versus patient-specific) might be underlying the unobserved portion of the prescription process. Details of the Gaussian Quadrature procedure are provided in Appendix B.[23]

Looking back at the formulation of the prescription choice in (6) and comparing it to its empirical counterpart, (10), it is clear that the empirical equation does not separately identify γ_1, the proportion of the patient's utility that is internalized by the physician. Given the data limitations, there is only one possible way of potentially identifying γ_1. Equation (10) assumes that the state laws on substitution affect physician's prescribing habits equally for all drugs. If, however, physicians perceive mandatory state substitution laws as eliminating the price differential between generics and trade-name drugs, then the price differential between the two versions of the drug depends on the type of substitution law in effect. This generates differences in drug prices across states that depend on the state in which the drug is being prescribed. According to this scenario, the effect of the dummy variable M in (10) should vary by insurance category and by drug class. A coefficient on an appropriate interaction term in the model might then be interpreted as a crude estimate of γ_1, since it would indicate whether physicians prescribe differently when the price differential is affected by state law. In addition, the implicit price differential can also be manipulated by the physician's choice of whether or not to forbid substitution on the prescription pad. In states with one-line substitution laws, physicians rarely forbid substitution and therefore rarely manipulate this price differential, while in states with two-line substitution, physicians more often forbid substitution. Once again this would imply an interaction between the substitution pad dummy variable and both the drug class and insurance variables. I briefly consider these possibilities in the empirical results.

6. Estimation results

■ The results of estimating the prescription-choice model (10) are given in Tables 4–6. This specification of the model includes eight drug-class dummy variables and a full set of interactions of these class dummy variables with the four insurance-status dummy variables. The omitted drug class is pain relief and the omitted insurance category is self-pay. Even with only these eight drug classes, the number of interaction terms is large, so that 53 coefficients are estimated. This explains the need for three tables to report the results of one regression. The sample size is 8,579 and the (pseudo) R^2 from the simple probit is .11. Clearly, there is a lot of variability in the prescription-choice decision that the model and the data do not capture.

[23] A final alternative estimation strategy is to assume that ϵ_{ij} has a logistic distribution and to estimate a conditional logit model. The conditional logit becomes computationally burdensome for large number of patients per physician, but conditional logit estimation with random subsamples of the data yielded estimates for the patient-specific coefficients similar to those reported below.

The first thing to note in Table 4 is that the estimate of ρ indicates that almost 30% of the unobserved (residual) variance in the prescription choice is physician-specific, rather than patient-specific.[24] This means that some physicians are more prone to prescribing generic drugs than others, and this cannot be explained by the observed characteristics of the physician, the patient, or, to some extent, the drugs prescribed. As Section 3 makes clear, it is highly unlikely that this is solely a function of physicians repeatedly prescribing the same form of a given drug, since the data contain few cases of multiple prescriptions of a given drug for a given physician. That is, this is predominantly a phenomenon where some physicians are more likely to prescribe generic versions of many or all drugs to their patients (even after controlling for observed physician and patient characteristics), while other physicians are more likely to prescribe trade-name versions.

Table 4 also contains the results for the estimated coefficients on the demographic and geographic variables, and the results on the coefficients of the average patient characteristics $\bar{X}_j$. The point estimates indicate that women are 2.11% less likely to be prescribed generics (significant at the 5% level), and nonwhites are 3.12% more likely to receive generics, although this latter result is not significant at standard levels. In addition, older people are significantly less likely to receive generics, even after controlling for their insurance status (which includes Medicare). There are a few possible explanations for these results. The first is that women and older people are more susceptible to potential quality differences between generics and trade names. For example, ensuring that elderly patients take their daily medications may require prescribing drugs of a readily identified color and shape. Another possible explanation is that these results are due to heterogeneity in the types of drugs prescribed to these groups versus other groups, and this heterogeneity is not captured by the drug dummy variables. There is some evidence that this is the case. For example, women are prescribed hormones that have generic substitutes, but these substitutes are seldom prescribed. The third possibility is that the demographic variables are proxies for omitted variables such as income of the patient, which may affect the proportion of the cost of the drug that the physician internalizes when prescribing. Whatever the explanation, the magnitude of these effects on the prescription decision is relatively small.

The results also suggest that patients in states with two-line prescription pads are only 1.25% less likely to receive "generically written" prescriptions, and this is statistically insignificant. In addition, while the point estimates indicate that physicians in mandatory substitution states are 4.30% less likely to prescribe generics than their colleagues in other states, this is also statistically insignificant. The small and insignificant magnitude of the effect of mandatory substitution laws is particularly interesting since in mandatory substitution states, a physician who writes a prescription for a trade-name version of a drug and does not prohibit substitution by the pharmacist should, in theory, be fairly certain that the pharmacist will substitute and that the patient will receive the generic. The lack of physician sensitivity to state laws has a few possible interpretations. First, to the extent that pharmacist substitution does not appear to occur as frequently as it should, physicians in all states may realize that writing a generic prescription is the only way to ensure that the generic is dispensed. Second, if the prescription decision is made without regard to price or the costs of learning about generics—that is, physicians prescribe generics for reasons having to do with their

[24] This implies that if one were to estimate a simple probit model and not correct the standard errors for the correlated physician effect, the standard errors would be far too small. Indeed, this is exactly what happens (in unreported results). Estimating the more efficient Gaussian Quadrature random-effects probit (as in the reported results) yields efficiency gains that reduce the standard errors to about what they are in the uncorrected probit.

TABLE 4 Estimated Coefficients on Demographic Variables, Geographic Variables, and Average Characteristics for Full Sample

Variable	Random-Effects Probit Coefficient	Random-Effects Probit *t*-statistic	% Change in Generic
Constant	.90	−5.15	—
Age	−.01	−3.72	−.10%
Female	−.07	−2.35	−2.11%
Nonwhite	.10	1.83	3.12%
Hispanic	−.02	−.18	−.70%
Specialist	.02	.40	.70%
Mandatory substitution	−.14	−1.90	-4.30%
Two-line prescription	−.04	−.72	−1.25%
Mean age	.00	1.45	.09%
Percent female	−.13	−.91	−4.08%
Percent black	.08	.50	2.37%
Percent Hispanic	−.16	−.81	−4.79%
Percent Medicaid	.20	.90	6.03%
Percent Medicare	.11	.48	3.29%
Percent private	.07	.60	2.05%
Percent HMO/prepaid	.33	2.32	10.12%
Midwest	−.18	−1.92	−5.80%
South	−.27	−3.04	−8.45%
West	−.02	−.17	−.52%
ρ	.29	14.85	

Notes: The dependent variable is one if the generic is prescribed, zero otherwise. The sample size is 8,579. The mean and percent variables refer to the mean and percent characteristics of the physician whom the patient visits. The omitted region category is Northeast. The omitted insurance categories are self-pay and percent self-pay. The percent changes in generic prescription are calculated as the average over the sample of the percent change in the probability of receiving a generic. For example, the percent change in the probability of generic prescription for age is the average percentage change for a marginal increase in age. For the dummy variables, the percent change in generic prescription represents the average percentage change that occurs when a person moves into the category represented by the dummy variable. The parameter ρ is the estimated variance of the random physician effect.

preferences or past experience with generics—then state legislation encouraging substitution by pharmacists will have little bearing on the prescription decision of physicians.

The coefficients on the regional dummy variables indicate that there are significant differences across regions in the propensity of generic prescription, with Southerners 8.45% less likely to receive generics than people in the Northeast. This is consistent with differences in information diffusion across regions—the usual explanation of this commonly seen phenomenon in health care (Phelps, 1992)—where information about the quality and availability of generics may diffuse at different rates across regions to physicians and to patients. This result is also consistent, however, with any other regional differences (such as differences in underlying preferences for generics or in the

training of physicians) that affect the prescription decision and that are not otherwise captured by the data.

The estimated coefficients on the mean characteristics are all insignificant at 5% levels, with the exception of the coefficient on percent HMO/prepaid. Although the interpretation of these mean coefficients can be problematic because they may not represent causal determinants of the prescription decision, the literal interpretation of the coefficient on percent HMO/prepaid is that, conditional on a patient's insurance status, a patient who switches to a physician with a marginally greater fraction of HMO patients is 10.12% more likely to receive a generically written prescription. There are a variety of possible interpretations of the magnitude and sign of this coefficient. First, it is entirely possible that the emphasis on cost containment in managed-care plans makes physicians more sensitive to prescribing generics. In many managed-care prepaid plans, physicians' salaries are tied to some measure of their productivity or merit (Luft, 1987) so that physicians who are perceived as costing the HMO "too much" may be penalized accordingly. Physicians therefore have an incentive to signal to the HMO that they provide low-cost care, and they may do this by prescribing generics. Moreover, because HMOs are heterogeneous in their treatment of pharmacist substitution, it is possible that the estimate of a 10.12% HMO effect is actually downward biased for those HMOs and prepaid plans that do not mandate pharmacist substitution. In cases where the HMO does not mandate pharmacist substitution, the physician's decision may have a direct impact on costs to the HMO, and this may give the physician a particularly strong incentive to prescribe generics.[25] Alternatively, this result may simply reflect self-selection of price-sensitive physicians or physicians with information about low-cost treatment alternatives into practices that treat patients covered by managed-care plans.

Table 5 contains the estimation results for the coefficients of the drug dummy variables. There are significant differences across drug classes in the frequency of generic prescription. This corroborates the results in Table 3 and illustrates that the differences in generic prescription across drug classes cannot be attributed solely to measurable characteristics of physicians or their patients.

The results on the tests of moral hazard in insurance are given in Table 6. For each drug class, the table reports the estimated coefficient on each of the insurance dummy variables, the t-statistic, and the percent change in the probability of a physician prescribing a generic for a patient who switches from having no insurance to being covered by each of the four insurance categories. The important result in this table is that few of the coefficients are estimated precisely, and the directions of the change in generic propensity by insurance class vary greatly across drug classes. That is, the results indicate that there is no strong evidence that the probability of receiving a generic varies systematically with the insurance status of the patient. Controlling for demographic characteristics of a patient and the patient's physician (in particular, controlling for the age of the patient and the percent of a physician's patients affiliated with an HMO or prepaid plan), as well as controlling for aggregate drug characteristics, effectively eliminates any differentials in generic propensity across insurance classes.[26]

[25] A similar bias could be occurring as a result of some HMOs using their market power to obtain price discounts from trade-name manufacturers, and subsequently allowing their patients to receive the trade-name versions of some drugs. The estimate would then be downward biased for those HMOs without such agreements.

[26] A joint Wald test of all of the coefficients in Table 6 does not reject their significance, but this is not particularly telling, since the signs of the coefficients vary. Moreover, for Wald tests performed for each type of insurance separately, only Medicaid is jointly significant, and this is driven by the large coefficient on skin/mucous membranes.

TABLE 5 Estimated Coefficients for Drug-Class Dummy Variable for Full Sample

Drug Class	Random-Effects Probit Coefficient	Random-Effects *t*-Statistic	% Change in Generic
Antimicrobials	.87	8.29	26.67%
Cardiovascular/renals	.41	3.09	10.59%
Central nervous system	.49	4.08	13.33%
Hormones/hormonal mechanisms	.83	7.15	25.23%
Skin/mucous membrane	−.72	−4.41	−10.04%
Ophthalmics	−.21	−.90	−4.07%
Respiratory tract	−.45	−2.65	−7.47%

Note: The omitted drug category is pain relief.

Of particular note in Table 6 is the fact that patients belonging to HMOs or prepaid plans are not treated differently from other patients by a particular physician. This result is mainly driven by the fact that the regression also controls for the percentage of the physician's patients who belong to an HMO or prepaid plan.[27] That is, controlling for the characteristics of the physician is key to the finding that there is no moral hazard in insurance. It is not the individual patient's insurance that matters, but the distribution of insurance types across all patients of a physician that is important. This once again underscores the importance of having information about the physician and all the physician's patients when examining the market for prescription drugs, and suggests that this type of information may also be important for other medical outcomes.

There is thus no evidence in the NAMCS data of moral hazard in insurance for multisource prescription drugs. There are, however, a number of caveats still to be considered. One is that the drug-class dummy variables, which interact with the insurance variables, are relatively aggregate. It is therefore possible that there is too much heterogeneity within these drug classes to effectively measure moral hazard that varies across drugs (within a given drug class). Nonetheless, there are reasons to think that the result of no moral hazard would hold up even with better data. First, to the extent that all the other results point to a finding that physicians do not respond to pecuniary incentives in prescribing, it seems unlikely that incorporating price data will yield results consistent with moral hazard in insurance. Second, other evidence on drug expenditures from the RAND Health Insurance Experiment, where individuals were randomly assigned to various insurance reimbursement plans, also indicates that there was no difference in the rate of generic prescriptions across insurance plans (Leibowitz, Manning, and Newhouse, 1985).[28]

Another potential caveat to the results is measurement error in the insurance classifications of patients. For example, 15% of patients in the drug sample are classified

[27] To illustrate this point, the *t*-statistic from a test of the equality in mean generic prescription rates between patients with no insurance and those belonging to an HMO is −2.26. This significant raw difference in means is misleading, as it masks the importance of the physician in the outcome.

[28] The results from the RAND Health Insurance Experiment show that there were no significant differences across insurance plans in the percent of prescriptions filled at pharmacies with generic drugs (Leibowitz, Manning, and Newhouse, 1985). More generally, the RAND study found that prescription expenditures *per physician visit* were uncorrelated with insurance plan.

TABLE 6 **Tests of Moral Hazard for the Full Sample Equality of Individual Insurance Variables with Self-Payment Random-Effects Probit Results**

Insurance Variable	Anti-microbials	Cardio-vasculars	Metabolics	Hormones	Skin/ Mucous Membranes	Ophthal-mics	Pain Relief	Respir-atory Tract
Medicaid								
Coefficient	−.05	.25	−.14	.32	1.04	.29	−.42	−.02
t-statistic	−.63	1.56	−.77	1.78	5.32	1.02	−1.53	−.09
% change	−1.88%	8.21%	−4.25%	12.40%	18.69%	5.80%	−7.18%	−.26%
Medicare								
Coefficient	−.18	.02	.03	.34	−.13	.24	.04	.12
t-statistic	−1.73	.14	.24	2.68	−.38	.93	.21	.47
% change	−6.46%	.50%	1.12%	13.22%	−.94%	4.63%	1.83%	1.66%
Private								
Coefficient	−.06	−.28	−.08	−.15	.22	.12	.20	.00
t-statistic	−1.08	−2.48	−.68	−1.46	1.14	.42	1.57	.00
% change	−2.45%	−7.89%	−2.48%	−5.51%	2.12%	2.27%	4.81%	.01%
HMO/Prepaid								
Coefficient	−.06	−.07	−.24	.04	.07	.12	−.14	.09
t-statistic	−.94	−.40	−1.20	.33	.28	.28	−.74	.37
% change	−2.45%	−2.22%	−7.26%	1.62%	.58%	2.11%	−2.77%	1.24%

Note: The percent change row represents the average percent change over the sample of patients in the probability of receiving a generic prescription when the patient's insurance status changes from self-pay to the appropriate insurance category.

as Medicare patients, but most of these patients also have other insurance (see the discussion in Section 2). Since Medicare does not pay for prescription drugs, classifying all of these patients as being covered by Medicare is potentially problematic. The same problem exists for the large number of patients classified as self-insured. Note, however, that this measurement error is real only if the physician actually knows the patient has other insurance that covers prescription pharmaceuticals. There is some evidence from Medicaid patients that this classification error is not biasing the results. Since physicians bill Medicaid directly for visits by Medicaid patients, and since Medicaid patients do not have other insurance coverage, the classification of Medicaid patients should be accurate. Yet the results for Medicaid patients in Table 6 also vary in sign across drug classes and are predominantly statistically insignificant. The same argument can be made for HMO/prepaid patients, where misclassification of insurance status should also be low.

To eliminate the problems inherent with the insurance classification of Medicare patients, and to account for the possibility that Medicare patients differ systematically from others in their prescription drug needs, I replicated the results in Tables 4–6 for the subsample of patients under the age of 65. The results (not reported here) do not differ substantively from the results for the entire sample. In addition, to account for possible measurement error in the mean-characteristics variables caused by observing only a subsample of each physician's patients, I estimated the model for those physicians who record data for more than 20 and, alternatively, 30 patients in the overall NAMCS sample. These results (not reported here) are also not substantitively different

from those for the full sample, indicating that measurement error in the mean-characteristics variables is not causing large biases in the results.

There are two potential reasons to be concerned about the inclusion of state laws in the estimation in Tables 4–6. As explained in Section 5, the inclusion of only linear terms for state substitution laws may not adequately capture their effect on the prescription choice if they change the effective price differential of the drug. Moreover, estimating a coefficient on an interaction between mandatory substitution laws and the drug dummies might arguably allow for separate identification of baseline differences across drugs from the proportion of the drug's cost to the patient that is internalized by physicians (the term γ_1 in the model). Rather than attempting to estimate and interpret regression coefficients from a model allowing for full interactions between drug dummies, insurance dummies, and the two types of state prescription laws, I indirectly account for this possibility by simply estimating the model with only the subsample of 4,334 observations from states with permissive substitution laws and one-line prescription pads. The results, reported in Tables 7–9, are quite similar to those for the full sample reported in Tables 4–6. This means that there is little difference in the treatment of patients across different regimes of state substitution and prescription-pad laws (so that γ_1 is essentially zero). Given that much of the variance in the prescription decision is unexplained, it is not surprising that differences across states in laws that may be poorly understood by physicians and poorly adhered to by pharmacists have little or no direct effect on prescription behavior. This result is nonetheless consistent with the conclusion that physicians internalize little of any differential costs to different patients.

7. Conclusion

■ This article examines the importance of physicians in the process by which patients get either trade-name or generic drugs. The central result is that the physician is an important agent in the prescription decision. This should be a key focus of future research, since the reasons for why some physicians are more likely than others to prescribe generic drugs is largely left unexplained by the empirical analysis presented here. Identifying the sources of heterogeneity in behavior across physicians is an important part of understanding how the market for prescription drugs operates and, more generally, how physicians behave when faced with different information and incentives.

One avenue for future research should focus on differences across drugs in generic prescription rates. A formal treatment of information diffusion would be a useful starting point for thinking about this issue. One possibility for examining diffusion empirically is to gather data on the length of time generics and trade-name drugs have been marketed and to incorporate such information into the model of prescription choice. Another element in the examination of the diffusion of generics would be to combine data from the NAMCS surveys in other years. At the time this article was written, the NCHS would not release to me physician-identifying data for years other than 1989.[29] It would also be useful to consider other dimensions of differences across drugs, such as their use in treating chronic versus acute conditions, or life-threatening versus mild conditions.

On the policy side, it is clear that there are potentially large social costs due to the habitual prescription of trade-name drugs. When physicians make prescription decisions based on incomplete information combined with agency problems, they do not make cost-effective decisions. Even state legislation that encourages generic substitution does not seem to have had an impact on physician prescription decisions. Changes in the structure of the health care system, however, may dramatically alter the market

[29] As of the 1991 NAMCS, the NCHS has included physician identifiers in the public-use data, but there is no information on the state in which the physician practices.

TABLE 7 **Estimated Coefficients on Demographic Variables, Geographic Variables, and Average Characteristics for Subsample from States with Permissive Substitution and One-Line Prescription Pads**

Variable	Random-Effects Probit Coefficient	Random-Effects Probit t-Statistic	% Change in Generic
Constant	−.31	−2.13	
Age	−.01	−3.60	−.15%
Female	−.10	−2.31	−3.08%
Nonwhite	.07	.77	2.29%
Hispanic	−.02	−.17	−.67%
Specialist	.00	.02	.05%
Mean age	.00	.87	.08%
Percent female	−.41	−2.00	−12.77%
Percent black	−.13	−.52	−4.02%
Percent Hispanic	−.60	−1.85	−19.77%
Percent Medicaid	.21	.77	6.59%
Percent Medicare	−.10	−.31	−3.24%
Percent private	.08	.50	2.60%
Percent HMO/prepaid	.20	.92	6.09%
Midwest	−.28	−2.08	−9.00
South	−.30	−.09	−9.56
West	−.05	−.36	−1.66
ρ	.25	8.98	

Note: The dependent variable is one if the generic is prescribed, zero otherwise. The sample size is 4,334. The mean and percent variables refer to the mean and percent characteristics of the physician whom the patient visits. The omitted region category is Northeast. The omitted insurance categories are self-pay and percent self-pay. The percent changes in generic prescription are calculated as the average over the sample of the percent change in the probability of receiving a generic. For example, the percent change in the probability of generic prescription for age is the average percentage change for a marginal increase in age. For the dummy variables, the percent change in generic prescription represents the average percentage change that occurs when a person moves into the category represented by the dummy variable. The parameter ρ is the estimated variance of the random physician effect.

for prescription drugs. Information from IMS America Inc., a market research firm, shows that managed-care payments (both private managed care such as HMOs and Medicaid HMOs) accounted for 58.5% of dollar revenues for pharmaceutical retail sales in 1996, up from less than 30% in 1990 (IMS America, 1996). Given the emphasis on cost containment in HMOs, the continued growth of managed care may increase the market share of generic drugs, or may cause the price differential between trade-name and generic drugs to fall as HMOs negotiate with trade-name manufacturers for price discounts. Other information from IMS (IMS America, 1995) indicates that there is some evidence that changes are already occurring. As of 1995, pharmacists substituted generics in approximately half of all cases where physicians wrote a new prescription for a trade-name drug for which a generic was available. This is up from less than 30% in 1989. Interestingly, however, while 44% of all new prescriptions (including

TABLE 8 **Estimated Coefficients for Drug-Class Dummy Variable for Subsample of States**

Drug Class	Random-Effects Probit Coefficient	Random-Effects *t*-Statistic	% Change in Generic
Antimicrobials	.97	5.53	30.42%
Cardiovascular/renals	.21	.88	5.02%
Central nervous system	.76	3.85	22.54%
Hormones/hormonal mechanisms	1.05	5.78	33.61%
Skin/mucous membrane	−.77	−2.59	−10.72%
Ophthalmics	−.26	−.74	−4.89%
Respiratory tract	−.66	−.88	−9.80%

Note: The omitted drug category is pain relief.

both single- and multisource drugs) were filled with generics in 1995, only 42.4% of prescriptions paid for by private managed care were filled generically. This may suggest that managed-care groups have successfully bargained for price discounts from trade-name drug manufacturers.

There is one important caveat to the potential social benefits of increased generic prescription. Reducing the returns to trade-name drugs may have an adverse effect on

TABLE 9 **Tests of Moral Hazard for the Subsample of States Equality of Individual Insurance Variables with Self-Payment Random-Effects Probit Results**

Insurance Variable	Anti-microbials	Cardio-vasculars	Metabolics	Hormones	Skin/ Mucous Mem-branes	Opthal-mics	Pain Relief	Respir-atory Tract
Medicaid								
Coefficient	−.06	.56	−.48	.37	.61		−.04	−.17
t-statistic	−.45	2.18	−1.67	1.37	1.45		−.13	−.21
% change	−2.31%	17.97%	−15.37%	14.30%	7.11%		−.90%	−1.24%
Medicare								
Coefficient	−.02	.37	−.16	.36	.32	.56	.13	
t-statistic	−.10	1.97	−.71	2.01	.71	1.49	.46	
% change	−.61%	10.91%	−5.60%	14.13%	2.87%	12.07%	2.89%	
Private								
Coefficient	−.01	−.01	−.14	−.20	.13	.20	.12	.10
t-statistic	−.13	−.07	−.91	−1.28	.40	.45	.55	.13
% change	−.51%	−.36%	−5.06%	−7.50%	1.03%	3.42%	2.62%	.94%
HMO/prepaid								
Coefficient	−.04	.17	−.17	−.12	.43	.28	−.06	−.05
t-statistic	−.32	.55	−.65	−.59	1.26	.53	−.21	−.03
% change	−1.38%	4.68%	−5.83%	−4.54%	4.31%	5.21%	−1.13%	−.41%

Note: The percent change row represents the average percent change over the sample of patients in the probability of receiving a generic prescription when the patient's insurance status changes from self-pay to the appropriate insurance category. Sample sizes in empty cells are too small to estimate coefficients.

pharmaceutical R&D investment and new drug development. There is little evidence on the magnitude of this effect, which suggests another important avenue for future research. Nonetheless, if the private returns to pharmaceutical R&D need to be supplemented to promote more efficient levels of drug discovery, the best mechanism to subsidize private drug development is probably not the indirect subsidies provided by market imperfections in the demand for prescription drugs.

Appendix A

■ The data for this article are taken from three versions of the 1989 NAMCS: the publicly available NAMCS for patient visits; a version of the NAMCS for patient visits with additional confidential identifying information; and the publicly available NAMCS for drug mentions. The NAMCS is a survey of approximately 1,200 office-based physicians and a subsample of their patients, conducted not-quite annually by the National Center for Health Statistics (NCHS). It is a three-stage sample of primary sampling units (PSUs), physician practices within a PSU, and patient visits within practices. A PSU is a county, group of counties, or standard metropolitan statistical area. After the first and second stages of the sample, selected physicians were randomly assigned to two consecutive weeks of the year beginning in February 1989, and they filled out detailed questionaires on a random subsample of patient visits during those two weeks. The average physician recorded data for approximately 30 patients, although there is a lot of variability in the number of patients per physician. The sampling scheme was designed so that physicians with larger practices recorded data for more patients, although not in fixed proportions to the overall sizes of the practices. (Physicians who saw fewer than ten patients filled out questionaires for all patients they saw.)

These questionaires contain data on demographic characteristics of the patient (age, sex, race, ethnicity) as well as data pertaining to his or her medical condition and details about what occurred during the visit such as duration of the visit, procedures performed, and diagnosis. In addition, the physician recorded for each patient the expected source(s) of payment for the visit: self-pay, Medicare, Medicaid, Blue Cross/Blue Shield, other commercial insurance, HMO/prepaid plans, no charge, or other. If the patient paid for the visit but was to be reimbursed by a third-party payer, the physician was told to only consider the third-party payer as the source of payment. Most importantly, the physician was instructed to list up to five medications ordered for the patient and to record "the same specific drug name (brand or generic) . . . used on any prescription." The definition of medications was interpreted broadly and included both prescription and nonprescription pharmaceuticals.

All three versions of the data contain the results of the questionaires as well as information identifying the specialty of the physician and the region of the country in which the physician practices (North, South, East, Midwest). In the publicly available 1989 NAMCS for patient visits and its confidential counterpart, the unit of observation is a patient visit, and patient-specific sampling weights are included in the data. The confidential NAMCS also links the patients of each physician together via a physician identification number and contains information on the U.S. state in which the physician practiced. The state identifiers allow prescriptions to be classified according to state laws about generic substitution, and the physician identifiers allow for the inclusion of physician-specific effects into the model. Although the public version of the NAMCS is available for other years as well, the confidential version of the data has only been prepared for 1989.

In the NAMCS for drug mentions, the unit of observation is an ordered medicine. Therefore, information is included only for those patients for whom a drug was ordered; for patients for whom multiple medicines were ordered, multiple observations appear (and these observations cannot be linked in these data). Because the drug-mentions data focus on medicines, drug-specific sampling weights are attached to each observation. In addition, these data contain information matching each ordered medicine to a unique trade-name drug code as well as a corresponding generic drug code. The data also include other information about the drug ordered such as the generic name, manufacturer (either generic or trade-name), prescription status (over-the-counter or prescription), and drug class code (one of 20 major classes such as opthalmics or neurologics).[30] In conversations with representatives at the NCHS, it became clear that the manufacturer codes for each drug are not entirely reliable. I therefore verified each manufacturer code using the 1991 *Drug Facts and Comparisons*, a comprehensive pharmaceutical industry source for drug information.

The two sources of sampling weights in the data are the patient weights from the NAMCS for patient visits and the drug weights from the drug-mentions data. Experimentation with these two sets of sampling weights yielded very little difference between unweighted and weighted estimates of any of the results in this article. All results reported here are derived without sampling weights.

[30] See Table 3 for a list of the drug codes used in the empirical analysis.

Appendix B

■ This Appendix contains the derivation of the full likelihood for the random-effects probit. Consider the NAMCS prescription-drug data. For physician j, the data can be described as

$$(G_{1_j}, G_{2_j}, \ldots, G_{I_j}, Z_{1_j}, Z_{2_j}, \ldots, Z_{I_j}, Z_j),$$

where G_{i_j} denotes whether or not patient i_j, who was prescribed a multisource drug, received the generic or trade-name version and Z_{i_j} is a vector of personal characteristics of the physician, the patients who received multisource drugs, and patients who did not receive a multisource drug. Define $\rho = \sigma_\nu^2/(\sigma_u^2 + \sigma_\epsilon^2)$, where σ_ν^2 and σ_ϵ^2 are defined as in Section 5, and define δ to be the vector of parameters to be estimated in (10). Then joint probability of the prescription decision physician j makes for all I_j patients, conditional on observables and conditional on the unobservable ν_j, is

$$\text{Prob}(G_{1_j}, \ldots, G_{I_j} | Z_{1j}, \ldots, Z_{1_j}, \delta, \rho, \nu_j)$$

$$= \prod_{i_j=1}^{I_j} \Phi((Z_{i_j}\delta/(1-\rho)^{1/2} + (\rho/(1-\rho))^{1/2}\nu_j)(2G_{i_j} - 1)).$$

The unconditional (on ν_j) likelihood for the problem is

$$L(\delta, \rho) = \prod_{j=1}^{J} \int_{-\infty}^{\infty} 1/\sqrt{(2\pi)}\, e^{-\nu_j^2/2} \cdot$$

$$\prod_{i_j=1}^{I_j} \Phi((Z_{i_j}\delta/(1-\rho)^{1/2} + (\rho/(1-\rho))^{1/2}\nu_j)(2G_{i_j} - 1))\partial\nu_j.$$

Notice that the likelihood contains only a one-dimensional integral rather than the standard I_j-dimensional integral of the multinomial probit. The reduction in dimensionality arises from the assumption that the errors across patients of a given physician are equicorrelated. This assumption is natural in this context because the patient data are essentially just multiple observations for each physician. That is, the patient data have no natural ordering such as a time dimension.[31]

Butler and Moffitt (1982) point out that for this type of likelihood function, Gaussian Quadrature, an efficient numerical integration procedure, can be used to evaluate the integral with high accuracy and relatively low computational cost. The key to using Gaussian Quadrature in this case is the Hermite Integration formula (see, for example, Press et al. (1986)),

$$\int_{-\infty}^{\infty} e^{-Z^2} g(Z)\, dZ = \sum_{p=1}^{P} w_p g(Z_p),$$

where P is the number of points at which the integral is evaluated, w_p is the weight given to the pth point, and $g(Z_p)$ is the function $g(Z)$ evaluated at Z_p. Any likelihood function containing a one-dimensional integral of the form in (7) can be expressed in discrete terms as a summation over evaluation points.

Taking the log of the likelihood function in (11), defining $\bar{\nu} = \nu/\sqrt{2}$, and using the Hermite Integration formula transforms the estimation problem for δ into a Gaussian Quadrature maximum-likehood problem of the form

$$\max_{\delta} \sum_{j=1}^{J} \ln \sum_{p=1}^{P} 1/\sqrt{\pi}\, w_p \cdot \prod_{i_j=1}^{I_j} \Phi((Z_{i_j}\delta/(1-\rho)^{1/2} + \sqrt{(2)}(\rho/(1-\rho))^{1/2}\bar{\nu}_p)(2G_{i_j} - 1)).$$

Given weights w_p and evaluation points $\bar{\nu}_p$ (which can be found in Abramowitz and Stegun (1964)), solving for $\hat{\delta}$ is a typical maximization problem. The Gaussian Quadrature results reported in the article were calculated using 20 evaluation points.

[31] If the data were ordered, one could relax the equicorrelation assumption. In that case, one would not reduce the dimensionality of the problem, and a feasible estimation strategy might involve using the method of simulated moments. See Keane (1994) and the references therein for details.

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