FACTORS INFLUENCING PHYSICIANS' WILLINGNESS
TO SUBSTITUTE GENERICS FOR BRAND-NAMES
WHEN PRESCRIBING ANTIMICROBIAL DRUGS

by

Robert E. Howard

Thesis submitted to the Faculty of the

Virginia Polytechnic Institute and State University

in partial fulfillment of the requirements for the degree of

MASTER OF ARTS

in

Economics

_____

Nancy Wentzler, Chairperson

_____   _____

William Porter   Brian Reid

May, 1997
Blacksburg, Virginia

ABSTRACT

Physicians often continue to prescribe brand-name drugs to their patients even when less expensive generic equivalents are available. In a 1994 study, Judith Hellerstein advances two hypotheses to explain this behavior. First, doctors may consciously conclude that certain brand-name drugs impart a relative therapeutic benefit that outweighs their higher cost. Second, physicians may choose to prescribe brand-name drugs without evidence of therapeutic superiority if neither they nor their insured patients bear the increased cost of these drugs. The second hypothesis implies that moral hazard is evident in physicians' prescribing behavior. Hellerstein's findings support neither hypothesis, but her estimation equation does not explicitly capture the effects of brand-name/generic price differentials and information diffusion on the probability of generic prescription. The author adapts Hellerstein's theoretical model to a modified estimation equation that incorporates these effects and uses it to create new estimates based on data on antimicrobial prescriptions from the 1994 National Ambulatory Medical Care Survey (NAMCS).

Unexpectedly, the results appear to affirm both hypotheses. The evidence for moral hazard is particularly strong, as self-paying patients are significantly more likely than patients with Medicare or private insurance to be prescribed the generics that are cheapest relative to their brand-name counterparts. The author also finds that certain popular antimicrobial drugs such as amoxicillin and sulfamethoxazole/trimethoprim are prescribed

in the same form (generic or brand-name) by most doctors to most patients. The market power exhibited by these preferred forms leads the author to conclude that they are "brands" in the economic sense.

ACKNOWLEDGMENTS

TABLE OF CONTENTS

I. INTRODUCTION

In "The Demand for Post-Patent Prescription Pharmaceuticals," Judith Hellerstein notes that physicians often continue to prescribe brand-name drugs for their patients even when pharmacologically equivalent generic drugs are available.[1]   Because generics are less expensive than their brand-name counterparts, Hellerstein posits that cost-savings to the patient is not the only factor that physicians consider when choosing between generic and brand-name drugs. The following are two of the hypotheses Hellerstein tests in an attempt to explain physician persistence in prescribing the costlier brand-name drugs:

- Physicians evaluate the relative efficacy of brand-name drugs and their generic substitutes and prescribe the brand-name drugs when they are associated with therapeutic gains that outweigh their relatively higher cost to the patient.

- Physicians tend to prescribe brand-name drugs, even without evidence of their therapeutic superiority, because neither they nor their insured patients bear these drugs' increased cost with respect to generic substitutes. If this hypothesis is true, Hellerstein argues, moral hazard is evident in physicians' prescribing behavior because they have little or no incentive to internalize the drug costs ultimately borne by insurers.

Hellerstein concludes that she does not have adequate evidence to support either hypothesis. She finds, for instance, that the demographic characteristics of both the physician and the patient have little impact on the physician's prescribing behavior. As a result, she doubts that physicians make judgments about the subtle qualitative differences

[1] Judith K. Hellerstein, "The Demand for Post-Patent Prescription Pharmaceuticals," National Bureau of Economic Research (NBER) Working Paper No. 4981, Cambridge, MA: December 1994.

between brand-name and generic drugs at the same time that they are insensitive to other, much more obvious, factors that bear on a prescription—such as the patient's age. Furthermore, she finds no evidence that physicians consider patients' ability to pay when choosing between generic and brand-name drugs. In particular, patients with private insurance were no more likely to be prescribed brand-name drugs than those covered under government insurance programs such as Medicare and Medicaid or those with no insurance at all. It therefore seems unlikely to Hellerstein that medical insurance has introduced moral hazard into the brand-name-versus-generic decision process. Since both of her original hypotheses are unsupported, Hellerstein concludes that physicians consistently prescribe the same version of a given drug simply out of habit.

In Hellerstein's discussion of enhancements that could be made to her research, she notes that her estimation equation lacks parameters that explicitly capture the effect of brand-name/generic price differentials or the effect of information diffusion on the probability of a generic prescription. An explicit measure of price differential is crucial because, according to Hellerstein's theoretical model, the gap between the price of a generic drug and its brand-name counterpart grows smaller as the perceived relative therapeutic benefit associated with the brand-name decreases. A measure of information diffusion is needed because the perceived therapeutic advantage of a given brand-name is unlikely to be fixed over time. This study represents an attempt to adapt Hellerstein's theoretical model to an amended estimation equation that incorporates price and

information diffusion effects. More details on the theoretical and practical considerations that motivate this study are provided in the next chapter.

II. THEORETICAL MOTIVATION FOR MODEL

AND PROPOSED METHOD OF ESTIMATION

Hellerstein states that her findings of habit persistence and lack of moral hazard would be better tested if she could take into account price differentials between brand-name drugs and their generic counterparts when estimating her model. Because she did not incorporate price differentials into her analyses, she could not explicitly test whether physicians weigh drug cost against perceived therapeutic benefit when prescribing. The availability of price differentials would also allow the moral hazard issue to be resolved more definitively. Patients with comparatively lower out-of-pocket prescription costs, such as those with private insurance, may not be more likely to be prescribed brand-name drugs when all prescriptions are considered, but they may be prescribed brand-name drugs more often in cases in which the brand-name drug is much more expensive than its generic substitute.

Hellerstein also touches on, but does not pursue, the idea of introducing information diffusion into her estimation equation. Specifically, her model contains a variable that captures how accurately a physician is able to gauge the quality difference between a brand-name drug and its generic counterpart, but her empirical measurement of the impact of this variable does not take into account the fact that a physician's store of knowledge about a given drug increases over time. One can more reasonably expect a

physician to accurately assess quality differences between a brand-name and a generic drug when the generic has been on the market for an extended period.

The intent of this study is to augment Hellerstein's work by incorporating price differentials and periods of market availability for generic drugs into the estimation of her model. To obtain my empirical results I used National Ambulatory Medical Care Survey (NAMCS) data, released by the National Center for Health Statistics (NCHS), just as Hellerstein did, but I employed the 1994 version of the data set rather than the 1989 version so that the results would be more timely. The 1994 NAMCS includes data on 33,598 patient visits conducted by 1,704 physicians during 1994. In addition to demographic information on the patient and physician, each record contains data on each drug prescribed by the physician during the course of the visit.

Once I had created a list of all brand-name and generic drugs mentioned in the 1994 NAMCS, I determined the period of market availability for each generic and located a price differential for each brand-name/generic pair. I derived the period of market availability for each generic drug by calculating the time elapsed between the drug's FDA approval date and the middle of 1994 (June 30, 1994 for computational purposes). FDA approval date information was readily available from the United States Pharmacopeial Convention (USP).

I culled price data from the *Red Book,* a comprehensive list of wholesale prices that pharmacists consult when ordering drugs. Because this data source was only

available to me in printed format, I found it too time-consuming to locate and to enter prices for the thousands of generic and brand-name drugs that are mentioned in NAMCS. I reduced the burden by restricting my analysis to prescriptions for drugs classified as antimicrobial agents. This drug classification includes antibacterial agents, antifungal agents, and antiviral agents. About 70 individual drugs available in just over 100 brand-name and generic forms fall into this category, so hand-entry of prices for this group was feasible. Furthermore, prescriptions for antimicrobial drugs account for almost 15 percent of all prescriptions recorded in the data, so sufficient observations were available for analysis.

I had to pare the original NAMCS data considerably to create a data set suitable for analysis. Of the 40,286 drug mentions on the 1994 NAMCS, only 4,587 are for prescription antimicrobials. Furthermore, 2,386 of these mentions are for drugs that were not available in both brand-name and generic form in 1994. These records had to be dropped from the analysis because the prescribing physician did not have to make a brand-name/generic choice. This left 2,201 available drug mentions, but 127 of these were ultimately excluded due to insufficient visit payment information for the patients who received those prescriptions. As is made clear in the next section, adequate payment information was needed to test for evidence of moral hazard. Thus the final analysis data set contains 2,074 observations.

III. THE MODEL

Hellerstein's model is represented by equation (1). She hypothesizes that physician j will prescribe the generic form of drug k to patient i if and only if

$$(1) \quad q_k^* + c_j + c_k < \Delta P_k (1 - \textbf{g}\textbf{q}_{ij})$$

where

q_k^* is the quality difference between the brand-name drug and the generic substitute for the kth drug;

c_j is the physician-specific component of the prediction error the physician makes when assessing the quality difference;

c_k is the drug-specific component of the prediction error the physician makes when assessing the quality difference;

ΔP_k is the price differential between the brand-name drug and the generic substitute;

$\textbf{g}$ is the proportion of the cost to the insurer that the physician does *not* internalize when deciding between brand-name and generic drugs (for example, if this parameter equals 1, the physician internalizes none of the cost to the insurer), which must be between 0 and 1 inclusive; and

$\textbf{q}_{ij}$ is the proportion of the cost of the drug covered by the patient's insurance, which must be between 0 and 1 inclusive.

9

When variables with similar subscripts are brought together and the equation is expressed in probabilistic notation, equation (2) is the result:

$$(2) \quad \text{Prob}[G_{ij} = 1 \mid \Delta P_k, q_k^*, c_j, c_k, \boldsymbol{q}_{ij}] = \text{Prob}[(\Delta P_k - q_k^* - c_k) - \Delta P_k \boldsymbol{g} \boldsymbol{q}_{ij} - c_j + \boldsymbol{e}_{ij} > 0]$$

where G_{ij} indicates whether physician j prescribed patient i the generic or brand-name form of drug k.

Hellerstein's next step is to adapt her model to the data that are available from the NAMCS:

$\Delta P_k - q_k^* - c_k$ may be interpreted as the price differential net of the two drug-specific effects, which are the quality differential between the brand-name and generic forms of drug k and the portion of the physician's prediction error that is attributable to the drug rather than to the physician. Intuitively, this term is equal to the quality-adjusted price of drug k. It is represented in Hellerstein's estimation equation as a vector $\boldsymbol{C}$ of drug class dummy variables. This reflects Hellerstein's implicit assumption, which she admits is subject to question, that price and quality differences between brand-names and generics do not vary within a given class of drugs (such as hormones or analgesics). I could not incorporate this assumption into my revised model even if I wished to because I am only analyzing prescriptions from one drug class, the antimicrobials.

$\Delta P_k \boldsymbol{g} \boldsymbol{q}_{ij}$ may be interpreted as the share of the price differential that is paid for by the patient's insurance but is not internalized by the physician who makes the prescription decision. This term is represented in Hellerstein's estimation equation as an interaction between the drug class dummy vector $\boldsymbol{C}$ and a vector $\boldsymbol{X_2}$ of insurance dummy variables. Hellerstein assumes that, controlling for drug class, insurance covers the same proportion of drug costs for all patients who have the same type of coverage.

c_j is represented by function (3):

(3) $S_j \boldsymbol{p}_1 + M_j \boldsymbol{p}_2 + T_j \boldsymbol{p}_3 + \boldsymbol{R}_j \boldsymbol{p}_4 + \boldsymbol{X}_j \boldsymbol{p}_5 + \boldsymbol{u}_j$

Because the physician-specific prediction error in the physician's assessment of the quality difference cannot be directly observed, Hellerstein attempts to estimate it using the observed characteristics of the physician. Specifically, S is a dummy variable indicating whether the physician is a specialist,[2] M denotes whether the physician's practice is in a state with mandatory generic substitution laws, T indicates whether the state uses two-line prescription pads (which allow the physician to sign on one line to prescribe the brand-name drug and the other to allow generic substitution), $\boldsymbol{R}$ is a vector of dummies used to identify the region of the country (Northeast, South, West, or Midwest) where the physician's practice is located, and $\boldsymbol{X}$ is a vector of the following characteristics of the physician's patients: their average age; the percentage who are female; the percentage who are non-white; the percentage who are Hispanic; and, for each type of insurance coverage recorded in the NAMCS, the percentage of patients with that coverage.[3]

---

[2] A specialist is a doctor who is not in general practice, family practice, or general pediatrics.

[3] I am not able to incorporate M and T into my estimation equation because 1989—the year of Hellerstein's data set—is the most recent year for which NCHS released data in the NAMCS on the state in which a physician practices. My understanding is that NCHS stopped doing so for confidentiality reasons. Hellerstein's results show that these two legislative attempts to increase the frequency with which generics are prescribed, mandatory substitution laws and two-line prescription pads, have had surprisingly little impact on physicians' propensity to prescribe brand-name drugs. Although it is unfortunate that I will not be able to support or dispute Hellerstein's conclusions, the evidence from her

Hellerstein also adds a vector X_1 of patient characteristics variables to the set of regressors in the estimation equation. X_1 contains the age of the patient and dummy variables for the patient's sex, race (white or nonwhite), and ethnicity (Hispanic or non-Hispanic). Hellerstein does not explicitly link X_1 to (2), her theoretical equation, so I presume that she included this vector simply to increase the explanatory power of her model.

Through these substitutions and additions Hellerstein arrives at (4), her estimation equation:

$$(4) \quad \begin{aligned} &P[G_{ij} = 1 \,|\, C_k, X_{1_i}, X_{2_i}, S_j, M_j, T_j, R_j, X_j] = \\ &P[C_k \boldsymbol{l} + X_{1_i} \boldsymbol{b} + X_{2_i} \cdot C_k \boldsymbol{g} + S_j \boldsymbol{p}_1 + M_j \boldsymbol{p}_2 + T_j \boldsymbol{p}_3 + R_j \boldsymbol{p}_4 + X_j \boldsymbol{p}_5 + u_j + e_{ij} > 0] \end{aligned}$$

Hellerstein assumes that both of the error terms are normally distributed, and thus that their sum can be normalized such that it is distributed N(0,1). The equation can then be estimated using a fixed-effects probit specification, but Hellerstein argues that random-effects probit is more appropriate here because the error terms associated with prescriptions written by the same physician are likely to be correlated.

---

paper suggests that the unavailability of state data will not significantly detract from the explanatory power of my model.

I propose to use Hellerstein's theoretical model, equation (2), but to substitute

different terms such that a new estimation equation is created:

ΔP_k is separated from the other terms and represented in my estimation equation as *L,* the natural log of the ratio of the generic price to the brand-name price. I used the ratio of the prices rather than their difference because the magnitude of the difference is heavily influenced by the dosage in which a drug is prescribed, which is not provided in the NAMCS data. In other words, I could not determine whether a given prescription was for a large or small amount of the drug or discern the product-form (such as tablet or capsule) in which the drug was prescribed. Brand-name/generic price differentials vary considerably based on dosage and product-form, but the ratio of generic price to brand-name price is largely unaffected by these superficial characteristics. The natural log of the ratio is used so that equivalent percentage differences in the ratio will have equivalent impacts. For example, the difference between the ratios 0.4 and 0.2 is equal to the difference between 1.0 to 0.8, but the first difference would represent a 50-percent drop in the relative price of the generic while the second difference would represent a drop of only 20 percent. Measured in logarithmic terms, the difference between the ratios 0.4 and 0.2 is equal to the difference between 1.0 and 0.5, as both are equivalent to a drop of 50 percent in the price of the generic form of a drug relative to the brand-name form.

$q_k^* + c_k$ can be intuitively understood as the consensus among physicians as to the quality differential between a brand-name drug and its generic substitute. (The assessment must be a consensus, and therefore independent of the physician writing the prescription, because the physician-specific component of the prediction error, c_j, has been split off for separate consideration.) I hypothesize that the medical community is risk-averse when faced with a new and untested product. As a result, physicians will attempt to overestimate the quality differential between a brand-name drug and its generic counterpart during the period when the generic is first introduced and the true quality differential is unknown. As time passes and the generic's performance is evaluated, the consensus quality differential will shift to more closely reflect the observed differential. Furthermore, because of the initial attempt at overestimation, the observed differential is likely to be lower than the original differential. The theoretical implication is that new generic drugs are associated with large consensus quality differentials and old generics are associated with small consensus differentials. (Expressed in economic terms, the longer a generic drug is on the market, the more it is perceived as a

substitute for its brand-name counterpart.) Based on this reasoning I used generic availability period as a proxy for the consensus quality differential. Accordingly, the combination of the quality differential term and the drug-specific prediction error term from the theoretical model is represented in my estimation equation as *A,* the natural log of the ratio of the number of days between the date the generic was approved by the FDA and June 30, 1994 to the total number of days between December 31, 1981 and June 30, 1994. Generics approved prior to 1982 are assigned a ratio of 1. Just as with the price ratio discussed above, the generic availability ratio is measured in logarithmic terms to render equal percentage differences in the ratio equivalent for purposes of the estimation.

$\Delta P_k \boldsymbol{g} \boldsymbol{q}_{ij}$ is represented in my estimation equation as the interaction of a vector $\boldsymbol{P}$ of price differential dummy variables with the vector $\boldsymbol{X_2}$ of insurance dummy variables that Hellerstein develops. The vector $\boldsymbol{P}$ contains two dummy variables. The first indicates whether the ratio of the price of the generic form of the drug to the price of the brand-name form is above the median price ratio calculated from the drugs in the sample. The second dummy variable is the complement of the first: it indicates whether the drug's generic-to-brand-name price ratio is below the median price ratio for the drugs in the sample. This method presumes that drugs with similar generic-to-brand-name price ratios are equally likely to be prescribed as generics, ceteris paribus, but that drugs with below-median price ratios are more (or less) likely to be prescribed in generic form than drugs with above-median price ratios. On the other side of the interaction, the five dummy variables in $\boldsymbol{X_2}$ record which of five types of medical insurance the patient used to pay for the physician visit at which the sampled prescription was written. The insurance types are HMO/other prepaid plan, Medicaid, Medicare, private/commercial insurance, and self-pay (no insurance used).[4] Based on my hypotheses, drugs with low generic-to-brand-name price ratios and drugs prescribed to uninsured patients are more likely than their respective counterparts to be prescribed in generic form. Thus the below-median price ratio/self-pay indicator was omitted for estimation purposes. The resulting coefficients on the other variables in the $\boldsymbol{X_2} \cdot \boldsymbol{P}$ interaction reflect the impact, ceteris paribus, on the probability of a given drug being prescribed in generic form with respect to low-price-ratio drugs

---

[4] Four other forms of payment are recorded in NAMCS: other government insurance (not Medicaid or Medicare), other insurance, payment method unknown, and no charge (visit was free). A prescription was excluded from the sample when written for a patient who was not charged or who paid for the physician visit exclusively through one of these methods. As noted above, 127 drug mentions were dropped on this basis.

prescribed to self-pay patients. If one or more of these coefficients is significant it may be construed as evidence of moral hazard or, in other words, that physicians are more likely to prescribe generics to uninsured patients than to patients holding certain types of insurance.

c_j is represented in my estimation equation by the function (3) developed by Hellerstein, except that I had to drop the *M* and *T* terms due to discontinuation of the variable Hellerstein used to determine the state in which a physician practices. See footnote3 for details.

Some of the independent variables incorporated into the estimation equation are not based on terms in Hellerstein's theoretical model. Most obviously, I retained the vector X_1 of patient characteristics variables that Hellerstein adds to her estimation equation. In addition, I inserted a dummy variable *O* into the equation to indicate prescriptions written for patients who received at least one other prescription for an antimicrobial drug during the same doctor visit. This variable is intended to capture variance caused by patients receiving multiple prescriptions. Failure to account for this effect might lead to correlation among the error terms associated with multiple prescriptions written for the same patient.[5]   Finally, I included a vector *D* of five individual drug dummy variables to flag prescriptions for amoxicillin, ampicillin, cephalexin, nitrofurantoin, and sulfamethoxazole/trimethoprim respectively.   Together

---

[5] Realistically, unobserved correlation across prescriptions written for a single patient is not a concern. Only three percent of the prescriptions in the sample were written for patients who received other antimicrobial prescriptions during the same visit. If unobserved correlation of this type were more of a concern, I might consider estimating a random-effects model with clustering of observations by physician and patient rather than simply by physician.

these five drugs account for 84 percent of prescriptions in the sample, and no other drug has more than 75 mentions among the 2,074 prescriptions in the analysis data set. Amoxicillin prescriptions alone represent 54 percent of all prescriptions in the sample. Because these drugs dominate the data, I repeatedly found evidence of a specification error when I attempted to estimate the model without incorporating drug-specific fixed effects. Adding *D* to introduce fixed effects for these five drugs significantly reduced the probability of a specification error, but it also caused the estimated coefficients for many of the other regressors to become statistically indistinguishable from zero.

The new estimation equation that results from my changes is shown as (5):

$$
\begin{aligned}
(5) \quad & P[G_{ij} = 1 \mid L_k, A_k, X_{1i}, X_{2i}, P_k, S_j, R_j, X_j, O_i, D_k] = \\
& P[L_k\, \boldsymbol{r} + A_k\, \boldsymbol{n} + X_{1i}\, \boldsymbol{b} + X_{2i} \cdot P_k\, \boldsymbol{g} + S_j\, \boldsymbol{p}_1 + R_j\, \boldsymbol{p}_2 + X_j\, \boldsymbol{p}_3 + O_i\, \boldsymbol{w} + D_k\, \boldsymbol{d} + \boldsymbol{u}_j + \boldsymbol{e}_{ij} > 0]
\end{aligned}
$$

IV. ESTIMATION RESULTS AND DISCUSSION

To maintain consistency with Hellerstein's methodology, I estimated the model via random-effects probit with clustering of prescriptions written by the same physician. The results are reproduced in a table in Appendix 1. Note the following when interpreting the table:

- The dependent variable in the regression equals 1 when a generic is prescribed and 0 when a brand-name is prescribed.

- The mean age variable and the seven "percent" variables represent the characteristics of the physician who wrote the sampled prescription.

- Self-pay/low-price generic, Northeast, and percent self-pay are the omitted categories.

- For continuous variables, which are marked with a "C," the percent change in the probability of a generic prescription is equal to the average percentage change, calculated over the sample, that results from a marginal increase in the variable's value.

- For dummy variables the percent change in the probability of a generic prescription is equal to the average percentage change that results, ceteris paribus, when a prescription's status shifts such that it within the category designated by the dummy.

Impact of Patient Characteristics

The results show that female patients are 3.5 percent more likely to be prescribed a generic antimicrobial drug than male patients, but the difference is not significant at the 5-

or 10-percent level. Nonwhites (African Americans, Asians, and Native Americans) are incrementally less likely (0.5 percent) than whites to be prescribed a generic, but Hispanics are much more likely (6.5) than non-Hispanics to receive a generic.[6]   Neither result is significant, however. Age and probability of receiving a generic are positively correlated according to the results, a 70-year-old being 7.9 percent more likely to receive a generic than a 25-year-old, ceteris paribus. Furthermore, the estimated impact of age on probability of generic prescription is significant at the 10-percent level.

These findings contrast with Hellerstein's, which indicate that being female or elderly significantly reduces the likelihood that a patient will be prescribed a generic drug. Hellerstein posits that she observed this effect because women and older patients are perceived by doctors to be more vulnerable to quality differences between generics and their brand-name counterparts. I found no evidence that this hypothesis is true for women, and at first blush my results argue that it is not true for the elderly either. The picture becomes more complex when the impact of insurance status is considered, however. Because of the large negative effect having Medicare has on probability of generic prescription, the estimated model actually predicts that elderly on Medicare are either equally likely or more likely to be prescribed a brand-name.[7]   Most elderly have

---

[6] Based on the definition applied for the purposes of the estimation, Hispanics may be of any race.

[7] A 70-year-old prescribed a drug for which a high-price generic is available is predicted to receive a generic or brand-name with approximately equal probability. A 70-year-old prescribed a drug for which a low-price generic is available is more likely to receive a brand-name according to my findings. See below for further discussion of the impact of insurance status and generic prices on the probability of generic prescription.

Medicare, so Hellerstein may be correct that physicians are wary of prescribing generics to older patients—but only when they are insured. The positive coefficient for age and the large negative coefficients for the Medicare regressors might indicate that doctors are much more attuned to the insurance status, or even financial circumstances, of their elderly patients than their younger patients. On the one hand, elderly who self-pay for medical visits are more likely than nonelderly self-payers to be prescribed a generic. On the other hand, those on Medicare, a program designed for the elderly, are much less likely than those with other types of insurance to be prescribed a generic.

The estimated effect associated with a patient receiving more than one prescription for an antimicrobial drug during a reported doctor visit is, happily, small and insignificant. This variable is included in the model to reduce correlation across prescriptions written for the same patient. Based on this result dropping the variable from the model would barely affect the other estimates, and it is doubtful that an estimator that accounts for clustering of prescriptions by patient is needed.

Impact of Physician Characteristics

The coefficient on the specialist dummy variable in my model is positive and significant, and indicates that specialists are 11.2 percent more likely than nonspecialists to prescribe an antimicrobial drug in its generic form. Hellerstein's estimate of the specialist

effect is positive, but it is also much smaller and insignificant. It is unclear why specialists would be more prone than nonspecialists to write prescriptions for generics. Visits to specialists are more expensive than visits to physicians in general practice, and many managed care organizations restrict access to specialists, so one would expect the clientele of specialists to be biased towards the wealthy and the heavily insured. In theory, those groups should be more likely to be prescribed brand-name drugs. This effect, if it exists, may have been captured by the insurance status variables, however. Conceivably, because the range of conditions they treat is narrower, specialists can focus their attention on a smaller number of drugs and thereby assess the effectiveness of promising new generics more quickly. By similar logic, specialists may be more able or willing than other physicians to keep themselves updated on the most recent developments in their field. Such research could serve as a substitute for clinical observation and lead to swifter acceptance of recently approved generics.

Unlike Hellerstein's findings, which indicate that probability of generic prescription is highest in the Northeast region of the United States, my findings show that physicians practicing in the West are 15.2 percent more likely than Northeastern doctors to prescribe a generic drug. Moreover, the difference is significant at the 10-percent level. Physicians in the Midwest are approximately equally as likely as those in the Northeast to prescribe a generic, but physicians in the South are 7.2 percent less likely. Hellerstein also finds that

Southern doctors are most reticent to write prescriptions for generics, but her estimate of the negative effect is statistically significant while mine is not.

Hellerstein attributes much of the regional difference to imperfect information diffusion, which may be motivating my results as well. Regional differences in the organizational structure of medical care providers might also play a role. Managed care organizations, which are commonly perceived as encouraging the prescription of generics as a way to cut costs, have achieved highest market penetration in California and the rest of the West, and lowest penetration in the South. The model is specified such that this effect is to be captured by the coefficient attached to the "Percent HMO or Prepaid" regressor, but this physician-level variable does not incorporate the effect of peer interaction. Information diffusion often occurs through word-of-mouth, and it is reasonable to expect that doctors gain information about the reliability and efficacy of newly marketed generics by discussing them with their colleagues. Furthermore, physicians are likely to have more interaction with peers who work near to them than with peers from other parts of the country. Under these conditions, non-HMO doctors working in a region with high HMO penetration are clearly more likely to interact with HMO doctors than non-HMO doctors working in a region with low HMO penetration. Thus, to the extent that HMO doctors have greater incentive to familiarize themselves with new generics (which is a contestable point that this study seeks to address), non-HMO doctors in high-HMO regions learn about—and perhaps become comfortable

with—new generics before their non-HMO counterparts in low-HMO regions. In my specification the region variables are most likely to capture this effect.

The estimated coefficients on the rest of the physician-level independent variables are insignificant. In other words, knowledge of the demographic composition and insurance status of a physician's patients reveals little about the physician's propensity to prescribe generic antimicrobials. Or, more specifically, such knowledge reveals little about the behavior of physicians in this particular sample because the information is also available at the patient level. My results offer no evidence that physicians compare patients to other patients with similar characteristics when making prescription decisions.

Impact of Drug Characteristics

The signs on the estimated coefficients for price ratio and availability ratio conform with the expectations cited in Chapter II: antimicrobial drugs become less likely to be prescribed in generic form as the relative price of the generic increases and more likely to be prescribed in generic form as length of market availability increases. Neither coefficient is significant, however.

It is possible, of course, that some of the price effect is being captured by the coefficients on the interaction of insurance status and price. But a closer inspection of these coefficients reveals that the effect associated with low-price generics is more

negative than the effect for high-price generics for every insurance category except self-pay. Thus, contrary to theory, when patients with the same type of insurance are compared, those prescribed drugs for which the generic form is more expensive relative to the brand-name are nonetheless more likely to receive a generic than patients prescribe drugs for which the generic form is relatively less expensive. The perverseness of this finding is mitigated, however, by the estimated negative impact of price ratio on probability of generic prescription. Specifically, the insurance status/price interaction coefficients on the one hand and the price ratio coefficient on the other hand have countervailing effects. This may be interpreted to mean that the price of a generic antimicrobial drug does not influence the likelihood that a physician will choose it over a brand-name.

The coefficients estimated for four of the five individual drug dummy variables are surprisingly large, and three of the five coefficients are highly statistically significant. Clearly fixed effects associated with individual drugs account for much of the model's explanatory power. When these regressors are dropped from the model, in fact, the probability of a specification error increases dramatically.

This result argues strongly for Hellerstein's conclusion that physicians' prescription behavior is largely explained by habit persistence. In other words, physicians tend to prescribe the same form (generic or brand-name) of any given drug to every patient regardless of the patient's characteristics. Based on my findings, however, certain

characteristics of the physician do influence which form is prescribed. In particular, specialists and physicians practicing in the West are more willing to choose generics. To a much greater degree than Hellerstein's, my results support the conclusion that physicians with characteristics in common share information about the efficacy of individual generics. Although other explanations are plausible, simple habit persistence among them, my model may be reflecting the consensus opinions on the desirability of individual generics that have been formulated within groups of associating physicians. For example, while the generic form of amoxicillin is widely accepted among all physicians, the results in Appendix 1 provide evidence (which an independent test confirms) that specialists are significantly more likely than nonspecialists to prescribe generic amoxicillin.

Evidence of Moral Hazard

The estimated effects associated with the dummy variables of the insurance status/price interaction vary noticeably, but all except one are negative as expected.[8] Only the coefficients for "Medicare/Low-Price Generic" and "Private/Low-Price Generic" are significant, however. These two estimates alone offer sufficient evidence of moral hazard nonetheless. When the drug being prescribed has a low-price generic, patients on

---

[8] The estimated coefficient on the "HMO or Prepaid/High-Price Generic" dummy variable is positive but small, and clearly insignificant.

Medicare are 23.5 percent less likely than self-pay patients to receive the generic. Under the same circumstances, patients with private insurance are 16.8 percent less likely than self-pay patients to receive the generic. Physicians are clearly more willing to pass on the costs of brand-name antimicrobials to private insurers or the Medicare program than to their patients.

The moral hazard theory does not explain why, for every insurance category but self-pay, drugs with high-price generics are more likely to be prescribed in generic form than drugs with low-price generics. As noted above, the price ratio may be capturing the price effect and confounding interpretation of the coefficients on the interaction of insurance status and price. Another mitigating factor is that, within each insurance category, the difference between the coefficient on drugs with high-price generics and the coefficient on drugs with low-price generics is insignificant. The temptation is simply to conclude that generic price is not a factor that physicians consider when prescribing antimicrobial drugs.

V. CONCLUSION

Hellerstein finds little support for the two hypotheses she forwards to explain physician behavior in choosing between generic drugs and their brand-name counterparts. On the one hand, she rejects the hypothesis that physicians make sophisticated judgments about the relative efficacy of generics because she discovers minimal evidence that prescription decisions vary by patient or even by physician. On the other hand, she rejects the moral hazard hypothesis because her estimated model shows that insurance status also does not reliably predict the likelihood of receiving a generic. After having incorporated prices and a proxy for information diffusion into Hellerstein's model, however, I find that there is at least some support for both hypotheses.

While my results concur with Hellerstein's that the effect of patient-level characteristics on the generic/brand-name decision is unclear, they also show that certain physician-level and drug-level characteristics are significant predictors. Specifically, specialists and doctors who practice in the West are more likely than their counterparts to prescribe generics, ceteris paribus. Furthermore, the most commonly prescribed antimicrobial drugs tend to be prescribed in the same form (generic or brand-name) by all physicians to all patients. This is evidence, though not proof, for Hellerstein's first hypothesis. In other words, my results support the conclusion that all doctors—and

27

particularly doctors who might be expected to associate with one another—share information and formulate consensus opinions about the reliability of particular generics.

Hellerstein argues that the tendency of physicians to prescribe the same drug in the same form to all patients is explained by habit persistence, while I believe that this behavior reflects the consensuses physicians form about individual generics, but it is possible that both conclusions are merely different interpretations of the so-called "brand effect." Specifically, when one of a set of close substitutes for a given good is associated with that good more closely than the others in the minds of consumers, it often holds market power as a result of its "brand" status. In the over-the-counter drug market, for example, Tylenol has brand status because it has better name recognition among consumers than acetaminophen, its generic form. If an antimicrobial drug is prescribed in brand-name form to most patients by most doctors, this may simply mean that one or more of the brands under which the drug is sold has brand status in the economic sense. The combination antibiotic known generically as sulfamethoxazole/trimethoprim is almost always prescribed as either Bactrim or Septra, both of which are brand-name forms. The brand status these two products have acquired may be due merely to the convenience of writing "Bactrim" or "Septra" rather than "sulfamethoxazole/trimethoprim." If an antimicrobial is predominantly prescribed as a generic, this might indicate (paradoxically) that the generic form of the drug has attained brand status. For example, none of the brand-name forms of the drug known generically as amoxicillin has better name

recognition than amoxicillin itself. Thus generic prescriptions dominate amoxicillin prescriptions written.

My findings also lend credence to Hellerstein's second hypothesis that moral hazard is exhibited in physicians' prescribing behavior. When prescribing an antimicrobial drug for which a low-price generic is available, doctors are far more likely to prescribe the generic form to their self-pay patients than their patients with Medicare or private insurance. Interestingly, moral hazard is not evident in the behavior of physicians when they write prescriptions for antimicrobial drugs with high-price generics. A potential explanation is that the incentive for a physician to treat highly insured and uninsured patients differently decreases as the price of the generic approaches the price of the brand-name. Another, somewhat more perverse, possibility is that physicians perceive price as a proxy for quality. This hypothesis, which is not testable within the scope of this study, offers a solution to the puzzle of why, for all except self-pay patients, drugs with high-price generics are more likely than drugs with low-price generics to be prescribed in generic form.

LITERATURE CITED

1994 Red Book. Montvale, NJ: Medical Economics Data, 1994.

Approved Drug Products and Legal Requirements. Rockville, MD: The United States
Pharmacopeial Convention, Inc., 1996. Vol. III of *USP Dispensing
Information, 16th Edition.*

Hellerstein, Judith K. "The Demand for Post-Patent Prescription Pharmaceuticals."
National Bureau of Economic Research Working Paper No. 4981. Cambridge,
MA: NBER, 1994.

National Center for Health Statistics, Centers for Disease Control and Prevention. "1994
National Ambulatory Care Survey Data File and File Documentation." Hyattsville,
MD: NCHS, 1996.

APPENDIX 1. ESTIMATION RESULTS

```
General estimating equation for panel data   Number of obs     =      2074
Group variable:              Physician ID     Number of groups  =       636
Link:                              Probit     Obs/group, min    =         1
Family:                          Binomial                 avg  =      3.26
Correlation:                 Exchangeable                 max   =        25
                                              Chi²(33)          =    261.24
Scale parameter:                        1     Prob > Chi²       =    0.0000
Pearson Chi²(2040):               2417.63     Deviance          =   1955.90
Dispersion (Pearson):            1.185114     Dispersion        =  .9587755
                    (Standard errors adjusted for clustering on physician)
```

Variable	Coef-ficient	Robust Standard Error	z	P>|z|	% Change in Proba-bility of Generic
Constant	-.8801	.3559	-2.473	.013	
Log of Price Ratio (C)	-.1405	.1378	-1.020	.308	-5.24
Log of Availability Ratio (C)	.2077	.3956	.525	.599	7.75
Age (C)	.0046	.0028	1.647	.099	0.17
Female	.0945	.0651	1.451	.147	3.52
Nonwhite	-.0147	.1078	-.137	.891	-0.55
Hispanic	.1706	.1414	1.207	.227	6.51
HMO or Prepaid/High-Price Generic	.0358	.4201	.085	.932	1.34
HMO or Prepaid/Low-Price Generic	-.2730	.2874	-.950	.342	-9.72
Medicaid/High-Price Generic	-.0349	.4406	-.079	.937	-1.30
Medicaid/Low-Price Generic	-.1598	.3087	-.518	.605	-5.79
Medicare/High-Price Generic	-.2754	.4667	-.590	.555	-9.70
Medicare/Low-Price Generic	-.7752	.3339	-2.322	.020	-23.54
Private/High-Price Generic	-.0588	.4293	-.137	.891	-2.18
Private/Low-Price Generic	-.4885	.2402	-2.034	.042	-16.81
Self-Pay/High-Price Generic	-.2090	.4327	-.483	.629	-7.52
Specialist	.2941	.1483	1.983	.047	11.16
Midwest	.0117	.1990	.059	.953	0.44
South	-.1958	.2108	-.929	.353	-7.20
West	.3957	.2123	1.864	.062	15.15
Mean Age (C)	.0012	.0053	.227	.820	0.05
Percent Female (C)	-.0310	.2149	-.144	.885	-1.16
Percent Nonwhite (C)	.0766	.2518	.304	.761	2.86
Percent Hispanic (C)	-.3085	.3640	-.848	.397	-11.51
Percent HMO or Prepaid (C)	-.4407	.3063	-1.439	.150	-16.45
Percent Medicaid (C)	-.6478	.4414	-1.467	.142	-24.18
Percent Medicare (C)	-.6531	.5025	-1.300	.194	-24.38
Percent Private (C)	.3209	.2981	1.076	.282	11.98
Multi-Prescription Patient	-.0552	.2855	-.193	.847	-2.04
Amoxicillin	1.0980	.4235	2.592	.010	38.66
Ampicillin	3.0544	.5310	5.753	.000	66.54
Cephalexin	-.1637	.1935	-.846	.398	-5.96
Nitrofurantoin	-.8283	.6800	-1.218	.223	-24.53
Sulfamethoxazole/Trimethoprim	-1.3194	.3626	-3.639	.000	-35.53

VITA

Robert E. Howard, born October 27, 1967, researched and wrote this thesis to complete a Master of Arts degree in economics at the Virginia Polytechnic Institute and State University. At the time of its composition, and during the preceding period in which he finished the requisite class work, he worked as a programmer and research analyst at Mathematica Policy Research in Washington, D.C. Robert also holds Bachelor of Arts degrees in history and comparative literature from Brown University. Between his undergraduate years and his tenure at Mathematica, Robert spent a year in Bochum, Germany on a Fulbright scholarship. While in Germany he met Leslie Clayton, a fellow program participant, whom he happily wed in 1992. At the time this thesis was submitted Robert had just begun work as a statistician for IMS America in Plymouth Meeting, Pennsylvania.