NBER WORKING PAPER SERIES

EMPIRICAL IMPLICATIONS OF PHYSICIAN AUTHORITY IN PHARMACEUTICAL DECISIONMAKING

Scott Stern
Manuel Trajtenberg

Working Paper 6851
http://www.nber.org/papers/w6851

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 1998

We are grateful to seminar participants at the 1997 AEA Winter Meetings, Princeton, Wharton, the NBER Productivity Lunch, the 1997 Industrial Organization of Health Care Conference, the MIT IO Lunch, the UCLA Pharmaceutical Economics seminar, and the NBER Industrial Organization meetings for insightful comments and suggestions. Ashoke Bhattacharjya, William Comanor, Tom Hubbard, Judy Hellerstein, Alison Keith, Ariel Pakes, Peter Reiss, and John Rust provided many useful suggestions. Excellent research assistance was provided by Paul Ellickson, Jeff Furman, and Propa Ghosh. This research was supported by Pfizer, Merck, and the MIT Program on the Pharmaceutical Industry. The views expressed here are those of the author and do not reflect those of the National Bureau of Economic Research.

Empirical Implications of Physician Authority
in Pharmaceutical Decisionmaking
Scott Stern and Manuel Trajtenberg
NBER Working Paper No. 6851
December 1998
JEL No. D23, I11, L23, L84

ABSTRACT

This paper studies the consequences of physician authority on pharmaceutical prescribing. Physicians engage in a costly process of "matching" patients to the drug which most suits their particular conditions and characteristics. The relative efficiency of this matching process results from the diagnostic skill of the physician along with the investments made by the doctor in learning about different drugs. While the underlying level of physician skill or knowledge cannot be observed, differences among physicians in terms of these attributes are reflected in their prescribing behavior. We provide evidence for two major findings regarding the exercise of physician authority in this context. First, there is substantial variation in the degree to which physician prescribing is concentrated (i.e., some physicians prescribe a more diverse portfolio of drugs than others). Second, this concentration is correlated with observable drug characteristics. In particular, concentrated prescribers tend to prescribe drugs with high levels of advertising, low prices, and high (lagged) market shares. Our empirical results provide evidence for the importance of both physician effort and diagnostic ability in the prescribing process. In particular, physicians who differentiate among their patients more finely are more likely to have less concentrated prescribing portfolios and to be less sensitive to information sources which promote the use of drugs for the "average" patient.

Scott Stern
MIT Sloan School
Cambridge, MA 02142
and NBER
sstern@mit.edu

Manuel Trajtenberg
Tel Aviv University
Tel Aviv 69978
ISRAEL
and NBER
manuel@post.tau.ac.il

I. Introduction

In recent years, the internal organization of health care decision making has come under increasing scrutiny. From the introduction of the DRG Medicare payment system in the early 1980s to the proliferation of physician review programs in the context of managed care more recently, the role of physician authority over health care choices has been the subject of much debate (Weisbrod, 1992). While much of the literature has focused on how the financial incentives facing physicians affect their treatment behavior (e.g., the induced demand hypothesis (McGuire and Pauly, 1991)), the non-pecuniary effects of physician authority have remained for the most part unexplored.

This paper addresses the economic implications of the exercise of physician authority in the context of pharmaceutical prescribing. Patients benefit the most from pharmaceutical treatment if and when physicians prescribe to each patient *the* drug that best fits her exact pathology. However, physicians may lack the requisite diagnostic skills to identify the specific condition of each patient, or may face insufficient incentives to gather the information required to engage in finely discerning prescribing. As a result, the portfolio of drugs actually prescribed may be biased away from the optimum, and moreover, these biases may be systematically related to some fundamental characteristics of physicians.

The main goal of this paper is to provide empirical evidence of such potential biases, their covariates and related manifestations. Physicians' prescribing expertise, and hence their discriminatory power in terms of which drugs to prescribe, rely upon two knowledge-related assets: diagnostic skills and information about drugs. We argue, first, that increases in the discriminatory power of physicians would likely result in a more diverse prescription portfolio. That is, physicians who discriminate well will "match" the characteristics of their patients more precisely to the drugs they prescribe. Empirically, this type of heterogeneity will show up as variation in physician-specific indices of concentration in prescribing. Second, we hypothesize that less discriminating physicians will tend to be more reliant on low-cost sources of information about drugs, such as advertising (detailing) and awareness of the overall popularity of a drug (e.g., measured

by lagged market share). Thus, physicians with less discriminatory power will tend to prescribe advertising-intensive drugs and drugs with high lagged market shares.

The fundamental attributes of physicians driving both of these effects (e.g., diagnostic ability, knowledge of drugs, discriminatory prowess) are unobserved to the econometrician. We therefore put forward an empirical framework whereby the joint occurrence of these two effects, concentration in prescribing and reliance on low-cost informational sources, constitutes indirect but compelling evidence of the underlying heterogeneity in the fundamental attributes of physicians. In other words, to the extent that both concentration in prescribing and drug choice are governed by a similar process, then physicians who exhibit a concentrated portfolio would also be likely to prescribe advertising-intensive drugs and drugs with high lagged market shares. Thus, covariation between concentration measures, and choices of drugs with those characteristics, would reflect the underlying heterogeneity in the degree to which physicians are able (or willing to make investments) to finely discriminate among their patients.

In order to implement this framework, we start by exploring alternative indices of physician concentration in prescribing, computed on the basis of the distribution of prescriptions over drugs for each physician. We begin with the Herfindahl, perhaps the most common index of concentration, but note two potential difficulties in the present context. First, the average number of observed prescriptions per physicians is rather small, and hence high concentration might be confounded for fewness. A physician with a small number of observed prescriptions may appear to be "concentrated" simply because of the small number of "draws" from which the concentration measure is calculated. Second, we would like to disentangle the simple fact of concentration (as measured by the Herfindahl) from "excess" concentration, that is, the degree to which a physician's prescriptions are more concentrated than the *market*.

We draw upon the recent work of Ellison and Glaeser (1997) on geographic concentration indices in order to address these issues. Ellison and Glaeser derive a geography-based industrial concentration index from a discrete-choice model of

locational choice. It is possible to draw a precise analogy between the choice over where to locate a plant and the physician's choice of which drug to prescribe. By mapping the Ellison and Glaeser results into the physician concentration problem, we are able to construct indices which correct explicitly for the observed number of prescriptions, and to compare results depending on whether we want to examine the absolute or "excess" concentration level of each physician.

The empirical analysis uses a sample of over 1,500 prescriptions in two therapeutic categories, depression and hypertension, taken from the National Ambulatory Care Survey of 1993 and 1994. We show that there exists substantial variation among physicians in terms of their degree of concentration, using the different measures of concentration. We then explore how the sensitivity to drug characteristics varies among physicians with different characteristics, particularly according to concentration. We do that in the context of a discrete choice (multinomial logit) model of prescription choice at the patient level. The results by and large conform to our hypothesis: more concentrated physicians exhibit larger probabilities of prescribing drugs with higher levels of advertising, and larger lagged market shares. There is also some weaker evidence (in the direction predicted by the theory) for the effect of drug price and favorable clinical recommendations in the scientific literature on the prescription probabilities.

To highlight the quantitative significance of these findings, we perform a series of counterfactuals, which examine how the probability of prescribing drugs with certain characteristics varies with the degree of physician concentration. The results are quite revealing. For example, among anti-depressant prescriptions, highly advertised drugs are 36.5% more likely to be prescribed by physicians with above-average concentration levels, compared to physicians with below-average concentration.

By examining the role of physician authority in pharmaceutical decision making, this paper builds on recent research by Hellerstein (1997).[1] Hellerstein carefully documents

[1] Coscelli (1998) also extends Hellerstein's analysis in the context of a dataset of Italian physician prescription behavior.

the existence of physician "habit" by examining whether individual physicians tend to prescribe branded or generic versions of a given drug across their patient populations. However, we broaden the scope of such research by drawing upon recent work which suggests that intermolecular substitution is a key element in understanding competition and diffusion in pharmaceutical markets (Stern, 1996; Ellison, et. al, 1997; Ellickson, Stern, and Trajtenberg, 1998). To the extent that the diffusion of new pharmaceutical innovations depends on the "filter" of physician prescribing behavior, it is important to understand how physicians use their authority over drug choice. This paper joins also a growing empirical literature on the role of discretion and authority in the context of "expert" services. Like auto repairmen (Hubbard, 1997) and stock brokers (Ellison and Chevalier, 1997), physicians exercise authority based on their certified expertise in a specialized area of knowledge associated with the delivery of a service. However, while prior research has focused mostly on the consequences of differences in *financial* incentives facing an agent with authority over decision making, this paper provides evidence about the use of authority in the context of a non-pecuniary agency relationship.

Section II describes the institutional context of pharmaceutical decision making, the main issues that arise when examining the use of authority, and the implications of authority for concentration and drug choice. Section III discusses the use of alternative concentration measures. Section IV presents a formal model of drug choice and derives the main empirical prediction of the paper – the expected covariation between concentration and certain drug characteristics. Following a data section, Section VI presents the main empirical results, documenting the covariation between concentration and drug characteristics, and in section VII, we highlight the quantitative importance of these results through counterfactuals. A final section offers concluding observations.

II. The Exercise of Physician Authority in Pharmaceutical Prescribing

Before turning to a detailed analysis of physician prescribing, it is useful to understand the institutional context of pharmaceutical decision making. Several features of the environment surrounding the prescription decision make it an attractive setting for studying the exercise of authority. First, the FDA regulatory process sharply limits the number of distinct drugs available for a given condition,[2] and changes in the choice set occur only occasionally. As well, in most cases the choice among drugs is discrete – a single drug is prescribed for the treatment of a particular condition.[3] Thus, the physician usually faces a well-defined set of alternative drugs when making a prescription choice for a patient. Moreover, physician authority over the prescription decision constrains patient choice. For most conditions, patients are required to receive a physician's prescription before a drug can be dispensed.[4]

Furthermore, in most health care delivery environments, the physician's compensation for a visit does not depend on which drug is prescribed. As a result, physician authority over drug choice probably does not yield the "induced" demand associated with other aspects of physician behavior (McGuire and Pauly, 1991; Gruber and Owings, 1996). As well, while the physician has a positive incentive to provide an efficacious solution (both to build a reputation for quality as well as to avoid malpractice exposure), drug companies have historically been limited in their ability to directly compensate physicians for prescribing a particular drug.[5] Taken together, these three factors (a small number of discrete choices, physician authority over the drug, and the lack of financial incentives to choose particular drugs) make pharmaceutical decision making an attractive setting for studying the economic implications of the exercise of authority.

---

[2] Except where noted, "drug" and "molecule" are used interchangably to mean a distinct FDA-approved molecule.

[3] Of course, there is variation in dosage and delivery method. However, we abstract away from those choices here to focus on the discrete choice of which specific molecule to prescribe.

[4] In contrast, physicians exercise significantly less authority over the decision as to whether the prescription is filled in the branded or generic form, or whether the patient complies at all (see Ellickson, Stern and Trajtenberg, 1998).

[5] This constraint has been weakened substantially with the rise of managed care and PBM (prescription benefit management) organizations which monitor physician prescribing patterns and provide incentives for physicians based on their overall prescription portfolio.

The Impact of Diagnostic Skill and Drug Knowledge on Prescription Behavior

Consistent with recent discussions of the economic forces impacting authority (Aghion and Tirole, 1997), we propose that the main costs faced by physicians in pharmaceutical prescribing are two key *informational investments*. First, the patient must be diagnosed, a process in which the physician relies on her developed diagnostic skills in conjunction with effort devoted towards gathering and evaluating information about each patient. Second, the physician relies on investment in knowledge about the alternative drugs available, that is, their pros and cons in the treatment of various conditions, published clinical findings about their interactions with various patient types, and experience with particular drugs with other patients.

These informational investments are critical for achieving a good "fit" between the specific condition of a patient and the characteristics of the drug prescribed. Moreover, they are complements. If the physician's diagnostic skills are poor (or if she has not invested substantially in diagnosis), then extensive knowledge of drugs would be of limited help in improving the precision of the prescription. Likewise, if the physician has excellent diagnostic abilities but knows little of the relative advantages of alternative drugs for different patients, then the fit between patients and drugs will hardly improve.

Differences among physicians in terms of their skill and investment level will have consequences for their observed prescription behavior and, in particular, for their degree of concentration in prescribing. As a baseline, consider the hypothetical notion of "optimal" prescribing, that is, prescribing that constitutes the best possible "fit" between the specific condition of each patient and the attributes of drugs, given all available information about both patients and drugs. This optimal prescribing behavior, when applied to a group of patients, would generate an optimal prescription concentration. However, when physicians distinguish less precisely among their patients, the concentration level of their prescribing will be sub-optimal relative to this "first-best." In particular, physicians will tend to prescribe similar drugs to dissimilar patients (from the perspective of a full information model), increasing their concentration level.

Informational Investments and Physician Agency

A related implication of this discussion arises when considering the incentives of physicians to make investments in drug knowledge. Since patients commonly have less information than their physician about the impact of particular therapies on particular diseases, we expect that physicians may engage in agency-like behaviour in their interactions with patients.[6] One mechanism by which agency may be manifested is through the discretionary (and partially unobserved) informational investments for which the doctor cannot be fully compensated for (except perhaps by the development of a long-term reputation for quality). For example, rather than keeping up with all the latest and most nuanced findings in the clinical literature, physicians may "underinvest" by relying on alternative, "cheap" sources of information, resulting in heightened responsiveness to such factors as the popularity of a drug or its advertising intensity.

This implies that physicians with superior diagnostic skills will have stronger incentives to invest in keeping up with the medical literature, since the payoffs to them are high in terms of improved prescription efficiency and patent outcomes. Conversely, physicians with poor diagnostic skills will not benefit much from investing in keeping up with the literature, and hence will tend to rely on coarser information. Over time, these mutually reinforcing forces will result in physicians gravitating towards a particular "type" with both high levels of skill and investment vested in the same individuals. Moreover, both the degree of concentration and the drug characteristics prescribed by a physician will reflect her underlying type, and will thus be related to each other (see Figure A). Consequently, our empirical focus is on the covariation of these two distinct empirical implications of physician authority.

[6] Moreover, it is costly to "shop around" for a physician who will be willing to pursue a particular treatment. As pointed out by Arrow (1963), the presence of asymmetric information between physicians and patients, in conjunction with search costs, leads us to believe that agency may be an important problem in the context of health decisiomaking (see also the recent discussion by Aghion and Tirole (1997)).

III. Measures of concentration in prescribing

We have referred informally to the degree of concentration in prescribing as an important characteristic of physicians that may be informative of more fundamental but unobservable features of physicians. An immediate question thus arises as to how to assess concentration in prescribing, in a way that would help us shed light on these underlying features. We can begin with the most widely used concentration measure in economics, the Herfindahl index,

$$(1) \qquad H_l = \sum_{j \in J} s_{lj}^2$$

where s_{lj} is the share of drug j in the prescription portfolio of physician l (J is the set of drugs available for a particular condition, e.g., hypertension). Thus, physicians that tend to prescribe the same few drugs to different patients will exhibit values of H_l close to 1, whereas those that finely distinguish between patients and hence tend to prescribe different drugs to different patients will exhibit low values of H_l ($0 \leq H \leq 1$).

The statistical properties of the index H are both well understood and analytically convenient. However, in the context of our sample, two potential issues arise in its use. First, there are relatively few observed patients per physician. For example, nearly half of the physicians in our sample made just 1 or 2 prescriptions (within each therapeutic category), and relatively few made 10 prescriptions or more (about 20% in Depression, and 7% in Hypertension). This fact makes it hard to tell apart "true" concentration (as a behavioral characteristic of physicians), from lack of actual variation due to insufficient opportunity to observe prescription behavior over a large number of patients. That is, physicians that made a small number of prescriptions will tend to exhibit high values of H, but that is not necessarily indicative of genuine high concentration.[7] Second, in addition to our interest in the absolute level of concentration, we would like to assess the degree to which a physician exhibits "excess" concentration relative the the underlying distribution of shares of drugs in the overall market. While the Herfindahl measures the

[7] In the extreme, all physicians with only one observed prescription will have $H = 1$ by construction.

"absolute" level of concentration, we need to correct for the overall market shares of each drug in order to assess whether a physician exhibits "excess" concentration.

To tackle these issues, we employ a two-pronged approach. On the one hand, we limit our analysis to physicians that made at least a threshold number of prescriptions,[8] ensuring that there exists enough variation in concentration *conditional* on the number of prescriptions (as well, we control explicitly for the number of observed prescriptions in the empirical work). On the other hand, we resort to alternative indices, based upon the recent work of Ellison and Glaeser (1997) (E&G hereafter), that obviate these issues altogether.

E&G derive a geography-based industrial concentration index from a discrete-choice model of locational choice, taking into account the overall geographic distribution of employment, and the fact that industries vary in the size distribution of firms. As it turns out, E&G's framework and consequent index can be mapped precisely into the evaluation of physician concentration, allowing us to correct explicitly for the varying number of prescriptions, and to compare the implications of absolute versus "excess" concentration of an individual physician. In order to derive indices appropriate for our case, we first review theirs in brief.

Consider the following elements determining the probability of locating a plant from industry l in area j, in the presence of both "natural advantage" and agglomeration spillovers:

- x_j: the share of total employment located in area j, $j=1,\ldots,J$.
- s_{lj}: the share of employment of industry l in area j.
- z_{il}: the share of firm (or plant) i in industry l, $i = 1,\ldots,N_l$.
- $\tilde{H}_l = \sum_k^N z_{kl}^2$: the Herfindahl index of concentration in industry l.

[8] We present results for a sample of physicians with 4 or more observed prescriptions. We have experimented extensively with other "cut-off" points and found the qualitative results to be robust to changes in the sampling scheme.

- γ_l^{na}: a parameter that captures the importance of "natural advantage" factors in the choice of location, normalized so that $\gamma_l^{na} \in [0,1]$
- γ_l^{s} : a "spillover" parameter, also normalized to the unit interval.

E&G show that, under a certain set of assumptions regarding the stochastic properties of the underlying variables (determining the profits to each firm of locating in each area),

$$(2) \qquad E(G) \equiv E\left[\sum_j (s_{lj} - x_j)^2\right] = \left(1 - \sum_j x_j^2\right)[\gamma_l + (1-\gamma_l)\tilde{H}_l]$$

where $\gamma_l = \gamma_l^{na} + \gamma_l^{s} - \gamma_l^{na}\gamma_l^{s}$ (see E&G, Proposition 1). The expression $E\left[\sum_j (s_{lj} - x_j)^2\right]$ captures the degree to which a particular region-industry displays "excess" concentration, above and beyond what would be expected by the "dartboard" analogy. Accordingly, γ_l stands for forces affecting the location of firms in industry l in favor of geographic concentration. Absent such forces, that is if $\gamma_l = 0$, and if the industry itself is not "concentrated" in the traditional sense, i.e. $\tilde{H}_l \approx 0$, then the industry location will replicate (in expected value) the overall geographic distribution of employment, and hence $E(G) = 0$.[9] Eq. (2) leads to the following estimator of γ_l, which is E&G's proposed index of geographic concentration:

$$(3) \qquad \gamma_l \equiv \frac{\sum_j (s_{lj} - x_j)^2 - (1 - \sum_j x_j^2)\tilde{H}_l}{(1 - \sum_j x_j^2)(1 - \tilde{H}_l)}$$

In order to apply (3) to the evaluation of concentration in prescribing, consider the following parallels:

- areas (j) $\Leftrightarrow$ drugs (j)
- industries (l) $\Leftrightarrow$ physicians (l)
- firms/plants (i) within industry (l) $\Leftrightarrow$ patients (i) treated by physician (l)
- x_j : share of drug j in the market
- s_{lj}: share of drug j among the prescriptions given by physician l.

[9] This is the limiting case for which Ellison and Glaeser suggest the "dartboard" analogy, that is, firms could be seen in their location decisions as shooting darts at a board, scaled according to the distribution of overall employment, the x_j's.

In other words, each prescription decision is analogous to the plant location decision with the baseline probabilities being determined by the relative market shares of different "areas" (drugs). By observing the same physician multiple times, we are able to estimate the concentration level for each physician ("industry"). Notice, however, that, since each patient is prescribed a single drug, $z_{il}=1/N_l$, where N_l is the number of patients seen by physician l, and hence $\tilde{H}_l = 1/N_l$.[10] Thus Eq. (3) simplifies to:

$$(4) \qquad \gamma_l = \frac{\sum_j (s_{lj} - x_j)^2 - [(1-\overline{H})/N_l]}{(1-\overline{H})(1-1/N_l)} = \left(\frac{N_l}{N_l - 1}\right)\left(\frac{\sum_j (s_{lj} - x_j)^2}{(1-\overline{H})} - \frac{1}{N_l}\right)$$

where $\overline{H} = \sum_j x_j^2$ stands for the market-wide Herfindahl. Note that, relative to the simple Herfindahl index as defined in (1), the index γ_l accomplishes two objectives. First, it accounts for the fact that different physicians make different number of prescriptions (N_l) and, in particular, it corrects for the fact that a small number of prescriptions confounds true concentration, thus addressing our concern about "fewness."[11] Second, it takes into account concentration in prescribing by physician l only insofar as it differs from the pattern of market-wide concentration (i.e., concentration increases in $|s_{lj} - x_j|$). That is, if a physician is highly concentrated around drugs that are very popular in the market (i.e. that have high x_j's) then her γ_l will nevertheless be low, since the difference between each s_{lj} and x_j will be small. For γ_l to be high, physician l must be prescribing relatively few drugs, *and* any concentration must be above that which could be expected by observing a distribution of market shares. In this sense, E&G's baseline index is a measure of "excess" concentration, which can be a virtue or shortcoming, depending on the question asked. Consequently, we propose another index, which focuses on the

---

[10] Note the distinction between $\tilde{H}_l$ and H_l: $\tilde{H}_l$ is how concentrated physicians are in terms of their patients (trivially $1/N_l$) while H_l is how concentrated physicians are in terms of the drugs they prescribe.

[11] That is, this index downweights measured concentration for small N_l. As $N_l \to \infty$, $\gamma_l \to \sum_j (s_{lj} - x_j)^2 / (1-\overline{H})$.

"raw" level of concentration while accounting for the fact that the number of observed prescriptions varies across physicians:

$$(5)\ \gamma_l^* = \frac{N_l}{N_l - 1}\left[\frac{\sum_{j\in J}(s_{lj} - 1/J)^2}{(1-\overline{H})} - \frac{1}{N_l}\right] = \frac{N_l}{N_l - 1}\left[\frac{H_l - 1/J}{(1-\overline{H})} - \frac{1}{N_l}\right]$$

That is, we take here as a benchmark not the observed market shares x_j, but the shares that would obtain if physicians picked drugs entirely at random, *1/J*. The second expression in (5) makes it clear that γ_l^* is simply a linear combination of an individual physician's Herfindahl that corrects for differences among physicians in terms of the number of observed prescriptions. In our empirical work, we use all three indices ((1), (4) and (5)), thus ensuring that our results are robust to the way concentration is measured.

IV. Unobserved Heterogeneity, Concentration, and Type of Drugs Prescribed

In our earlier discussion, we suggested that both concentration in prescribing and drug choice may be governed by a common set of factors, and hence physicians who maintain a concentrated portfolio would be likely to prescribe certain type of drugs, e.g. those with high advertising and high lagged market shares. Thus, covariation between concentration measures and choice of drugs with those characteristics would constitute evidence of the extent of heterogeneity in the ability and incentives of physicians to finely discriminate among their patients. We now cast this hypothesis in terms of a discrete choice model, which allows us to establish more formally the connection between the concentration measures and the type of drugs prescribed.

Consider physician l choosing a drug for patient i who suffers from a given medical condition. We can write this as a simple discrete choice problem,

$$(6)\qquad \max_{j\in J} V_{i,j}^{l} = \theta_l \delta_j + \varepsilon_{i,j},$$

$$\delta_j = Z_j\beta + \alpha p_j$$

where Z_j are the drug characteristics which impact the perceived benefits of drug j for an "average" patient, and p_j is the price of drug j.[12] Thus, δ_j includes the overall popularity of a drug (as captured, say, by lagged market share), the level of advertising, the price, and the degree to which the clinical scientific literature contains positive information about the drug. The parameter θ_l captures the relative weight that physician l gives to δ_j in her decision making process, compared to the (unobserved to the econometrician) characteristics of patients and specific drug effects (beyond those in Z), as captured by the independent, idiosyncratic shock term, ε_{ij} (for convenience, we asumme ε_{ij} is distributed according to the Type I Extreme Value distribution).[13]

We use (6) to derive the relationship between the (unobserved) parameter θ_l and observed measures of concentration and drug choice. Let s_{lj} be the choice probability of drug j in physician l's prescription portfolio and $E(\delta_j)_l = \sum_{j \in J} s_{lj}\delta_j$.

Proposition 1: H_l, γ_l^* and $E(\delta_j)_l$ are increasing in θ_l.

After controlling for observable attributes of patients, physicians with higher levels of θ_l will tend to prescribe, (*i*) in a more concentrated fashion (where concentration can be measured by either of our "raw" measures of concentration, H_l or γ_l^*) and (*ii*) a portfolio of drugs with a higher mean value of δ_j. The argument is straightforward (see Appendix A for the proof). If the error term is independent, individual prescription probabilities, s_{lj}, are increasing and rank-ordered in δ_j. Both $E(\delta_j)_l$ and H_l are simply sums, weighted by s_j, over δ_j and s_{lj} respectively. Physicians who place more weight on the non-idiosyncratic portion of the utility will skew their choices towards drugs with higher values of δ. Therefore, $E(\delta_j)_l$ will increase as a result of reweighting towards drugs

[12] We could of course specifically incorporate the presence of unobserved product quality into the analysis (Berry, 1994). However, our focus is on interaction effects above and beyond the "average" prescription probability and so we abstract away from this in our analysis.

[13] Clearly, we could equivalently state the problem as: $\underset{j \in J}{\text{Max}}\ V_{i,j}^l = \delta_j + \sigma_l \varepsilon_{ij}$, $\sigma_l = 1/\theta_l$. As well, we abstract away from interactions between observable patient characteristics, X_i, and observable drug characteristics, Z_j in our theoretical discussion. We include such controls in the empirical analysis.

with larger δ_j's. Similarly, H_l will increase as a result of reweighting towards drugs with higher s_{lj}'s. As well, γ_l^* is simply a weighted sum of H_l, and so will also increase in θ_l.

Of course, Proposition 1 is a statement about the unobservable factors embedded in θ_l. However, it suggests that the variability of θ_l among physicians induces distributions in H_l, γ_l^*, and drug choices across physicians, and these distributions are related to each other, leading to the following empirical corollary:

- $Cov(H_l, \mathrm{E}(\delta_j)) > 0$ and $Cov(\gamma_l^*, \mathrm{E}(\delta_j)) > 0$.

In other words, physicians with higher measures of absolute concentration will tend to prescribe drugs with higher values of Z and lower prices (since the coefficient on price is expected to be negative). This is the key empirical implication of the model; we test for these effects through the inclusion of an interaction effect between individual drug characteristics and the physician concentration measures in a multinomial logit model of drug choice.

As well, we extend our analysis to analyze the implications associated with the measure of "excess" concentration, γ_l. As discussed in the previous section, this concentration measure is derived from a discrete choice model of locational choice for a plant within an industry which is precisely analogous to the choice of a physician choosing a drug for a particular patient. However, as opposed to H_l and γ_l^*, γ_l also accounts explicitly for the overall distribution of market shares in its calculation of the concentration index. This correction yields both (a) a more stringest test of our the underlying link between concentration and reliance on "low-cost" information sources and (b) introduces "noise" which leads us to expect a weaker statistical relationship between γ_l and Z_j. Consider the forumula for γ_l in the (asymptotic) case of an infinite number of observed prescriptions:

$$(7) \qquad \gamma_l \rightarrow \frac{\sum_{j \in J} (s_{lj} - x_j)^2}{1 - \bar{H}}$$

A high value of γ_i can arise in three distinct ways. First, a physician may be concentrated in precisely those drugs which themselves have high market shares (even relative to high x_j). Second, a physician may be concentrated in drugs which are in fact unpopular at the market level (i.e., those drugs with low x_j). Finally, a physician may simply have a more *balanced* prescription portfolio than the market (leading to large values for $|s_{ij} - x_j|$). In the first two cases, the relationship between γ_i and Z_j depends on whether or not the physician combines concentration with a tendency to prescribe drugs which embed low-cost information sources; our earlier discussion suggests that such interactions reflect the impact of physician talent along with the incentives to invest in high-cost information about drugs. On the other hand, to the extent that a high value of γ_i simply reflects more balance than the market (i.e., more even shares), then the relationship between γ_i and Z_j is ambiguous; this measure thus includes a source of "noise" in the underlying statistical framework. As a result, a finding that the covariation between drug characteristics and concentration is robust to the use of this measure of "excess" concentration provides support for the idea that observed differences in concentration reflect underlying differences in physician behavior which reflect themselves both in the differentation of patients by a physician and the use of different types of information sources about drugs. Moreover, our use of this measure sets a higher "bar" for our empirical work; we both expect this relationship to be weaker and interpret evidence along this dimension as a critical additional test of our underlying theory.

V. Data

To explore the impact of physician authority on prescription behavior, we employ the 1993 & 1994 National Ambulatory Medical Care Survey (NAMCS). The NAMCS is a publicly available, national survey of office-based physicians collected on an almost-annual basis by the National Center for Health Statistics (NCHS). The survey records approximately 35,000 patient office visits per year with approximately 2,500 physicians.[14] The NAMCS file contains the following information: (1) patient-specific

[14] NAMCS questionnaires are completed by participating physicians, who are selected from stratified Primary Sample Units (PSUs) and by specialty. Physicians are randomly assigned one week during the year, during which they record a systematic random sample of office visits.

medical condition and demographic characteristics; (2) physician-specific information including specialty; (3) expected sources of payment (HMO, Medicaid, Medicare, private insurance, self-payment, etc.); and (4) treatment-specific information regarding visit duration, recommended medications, diagnostic/therapeutic services, and whether the patient has been seen by the physician before.

The unit of observation in the NAMCS is a patient visit. Each record includes the physician's diagnoses of the patient as well as up to five medications prescribed by the physician.[15] For each medication ordered, the NAMCS provides the trade and generic names, specific trade and generic code numbers, prescription and controlled substance status, drug class (one of 20 major categories), and an indicator of whether the physician ordered the generic or trade product during the visit.[16]

This paper examines physician prescription behavior in treating depression and hypertension. We construct our dataset by examining patients who are diagnosed in one of these categories, and are issued a drug in the relevant classes. For each category, we have constructed the relevant drug set through a careful examination of the medical literature (*Physician's Desk Reference*, *Drug Facts and Comparisions*, *FDA Orange Book*).[17] Finally, because we are interested in drug choice, we group branded and generic versions of all drugs, yielding a dataset composed of choices over "molecules."

Since the NAMCS samples only a small subset of any physician's total patient population, many physicians are only observed prescribing a small number of times to patients with a particular condition (e.g., in the hypertension category, 113 physicians are observed only once). As discussed earlier, any measure of concentration which includes these physicians may be subject to bias, as the measure would confound differences

[15] Since medications and diagnoses are not paired, the possibility exists that where patients have multiple conditions and receive multiple medications, the matching of reason/diagnosis with medication will not be unique.

[16] Hellerstein (1997) uses this element of the NAMCS to characterize the role that physicians play in reinforcing trade-name market power.

[17] There exist a few drugs for which it was not possible to obtain meaningful drug-specific information (no price, advertising, etc.). We included these drugs in our calculation of the concentration measures for each physician but excluded these patients from the regression analysis.

among physicians in terms of the number of observed prescriptions and real differences in the level of concentration. Accordingly, we restrict our analysis to those physicians for whom at least 4 prescriptions are observed (in the therapeutic category of interest), yielding an average number of prescriptions of nearly 11 in the depression dataset and over 8 in hypertension.[18]

Tables 1 provides summary information of the data, encompassing three different dimensions: drugs, physicians and patients/prescriptions. The depression and hypertension datasets are composed of 1015 and 552 prescriptions divided among 97 and 82 physicians, respectively. There are 20 drugs available in the depression category and 27 drugs available for hypertension. The main variables associated with physicians are their concentration measures, and whether or not they are specialists. We compute for each physician the three alternative indices discussed in Section III: the Herfindahl, γ and γ^*. Note that there exists significant variation in each of the indices, as captured by their standard deviations (relative to their means), and that these are higher in depression than in hypertension. Note also that while the depression dataset is composed mostly of specialists, there are relatively few specialists in the hypertension dataset (just 17%).

As to drug-related variables, we consider several characteristics which may proxy for the use of "cheap" information by physicians, including the level of recent advertising, lagged market share, and the share of clinical articles positively recommending the use of the drug.[19] In addition, we calculate the average branded price for each drug: to the extent that the average patient bears some of the costs of purchasing the prescribed drugs and hence would prefer *ceteris paribus* less expensive drugs, less nuanced physicians may substitute into cheaper drugs.

---

[18] While this selection of course reduces our number of observations, we emphasize that the main qualitative results are robust to other cut-off points.

[19] The advertising measure is the total level of promotion in each year as reported in the IMS Journal, Mail and Detailing Audit. The prices are the average wholesale prices as reported in the Drug Topics Red Book (1993, 1994). The lagged market shares are based on prescription data from the 1991 NAMCS survey. Finally, the clinical literature variable was collected by an MIT undergraduate with a background in biology who coded five years of articles using abstract information in the MEDLINE database.

"controls." Note that the distribution of demographic characteristics seems to reflect the disease-specific biases implied by the clinical literature (e.g. older patients in hypertension, fewer male patients in depression, etc). The distribution of insurance status is also of interest, and conforms to common priors regarding each of the medical conditions (e.g. many more Medicare patients in hypertension than in depression, the converse for self-insured). While the patient insurance variable captures whether just the *visit* is insured, presumably patients who are uninsured for physician visits are uninsured also for pharmaceutical expenditures.

In order to highlight the extent of variation in the degree of concentration in prescribing, we present in Figure B the distributions of each of the concentration indices, for both depression and hypertension. Once again, it is clear that there is significant variation in each of the indices across physicians. This is a significant finding in itself that may reflect, as argued above, important differences in the underlying attributes of physicians regarding their skills and knowledge. Interestingly, the distributions for γ and γ^* appear to be more disperse than that of the Herfindahl. What this implies, reassuringly, is that the variance in the number of prescriptions per physician is not the main factor driving the variance in concentration. It seems also that the distributions of the indices for depression are more dispersed (i.e. flatter for the same range) than for hypertension.

As well, each of these concentration measures is closely related to one another. In Figure C, we map each of the "corrected" measures of concentration against the simple Herfindahl measure. In both categories, there is a close relationship between γ or γ^* and the Herfindahl measure, and, not surprisingly, this relationship holds more closely for γ^* than for γ.

Before turning to the formal empirical analysis, it is worth presenting a simple cross tabulation that hints at the key implications of our model. In Table 2, we divide the sample within each therapeutic category into two groups of doctors according to whether their Herfindahl measure is above or below the median Herfindahl (i.e., "High" or

"Low"). We then compare the mean characteristics of the drugs prescribed by these physicians. The differences are suggestive. Within each category, physicians with high values of the Herfindahl prescribe drugs with higher (lagged) market shares, higher advertising, lower prices, and higher shares of positive clinical recommendations. These differences are particularly large in Depression (e.g., high-Herfindahl physicians prescribe drugs with 50% higher advertising, 40% larger lagged market shares, etc).

VI. Concentrated Prescribing and Drug Characteristics

We now turn to the main empirical exercise of this paper – relating the degree of physician concentration to the type of drugs prescribed. We do that by estimating a conditional multinomial logit at the individual prescription/patient level, including a full set of drug dummies (which serve as controls and absorb any differences in the overall demand for different drugs).[20] All additional regressors take the form of interactions between drugs characteristics (e.g. previous market share, price, etc.) and the characteristics or either (a) patients (age, insurance status, etc.) or (b) physicians (concentration measures, specialist, etc.). In other words, the model estimates the (conditional) probabilities of being prescribed each of the drugs available to treat depression or hypertension, as a function of the interactions between drug characteristics and the attributes of each patient and her physician (beyond the baseline probability captured by the inclusion of drug fixed effects).

The interactions between patient and drug characteristics are of some interest in themselves (particularly those between insurance status and price), but for the most part they are included as controls. Different physicians may differ systematically in the type of patients they see, and we expect that their portfolio of prescriptions would reflect such heterogeneity. Thus, we would like to account as much as possible for the observable characteristics of patients, so as not to confound patient heterogeneity with the proclivity of different types of physicians to prescribe different types of drugs. We focus on the latter concept, and we estimate the size of this effect through interactions between drug

[20] We have also estimated the model with drug characteristics instead of drug fixed effects, and the qualitative results are essentially the same as reported below. The specification with fixed effects allows us to focus purely on the interaction effects, which are the object of interest in this paper.

charcacteristics and physician attributes, primarily the observed physician concentration level.

Tables 3-5 present the results for each alternative concentration measure (Herfindahl, γ^*, and γ), and Table 6 summarizes the main findings for the 3 measures. For expositional compactness we do not report in these tables the estimates for the drug fixed effects or the estimates for interactions between patient demographics and drug characteristics (see Appendix B for a full set of estimates (which also includes several additional controls). Each estimate in these tables refers to the interaction between a drug characteristic (a column), and a characteristic of patients or physicians (a row). For example, in Table 3A the negative coefficient for the advertising/specialist interaction (–0.017, and significant) means that specialists exhibit a lower probability of prescribing drugs that are heavily advertised, controlling for the overall attractiveness of each drug (i.e. the fixed effects), and for other relevant interactions. When using the Herfindahl we include also the number of prescriptions made (# of RX) as one of the physician attributes, but we omit it for the other two concentration measures. As explained in section III, the Herfindahl may be sensitive to the number of prescriptions (when these are few) and hence we explicitly control for this, whereas the γ indices incorporate # of RX and hence control directly for differences between physicians in that respect.

The estimates for depression (Table 3A) indicate that the interactions of the Herfindahl with both market share 1991 and advertising are positive and highly significant; similar results obtain for hypertension (Table 3B), though at a somewhat lower significance level.[21] Thus, more concentrated physicians tend to prescribe drugs with higher previous market shares and higher advertising levels. Moreover, while not statistically significant in this specification, the interactions of the Herfindahl with both price and positive science exhibit the correct signs (- for price, + for positive science). Taken together, these results are consistent with our leading hypothesis, namely, that physicians displaying a more concentrated prescription behavior tend to be more sensitive to drug characteristics

[21] Notice though that the estimates for Herfindahl×Advertising are very close in the two therapeutic categories: 0.030 and 0.027.

that apply to the "average" patient in the population. By contrast, physicians with lower Herfindahl indices are less likely to prescribe "popular" or heavily advertised drugs, and by implication will tend to pay more attention to other (presumably more specific) attributes of drugs and patients.

The results regarding the interactions with "specialist" in the depression category are worth noting: specialists are less likely to prescribe heavily advertised drugs, and more likely to prescribe drugs that have received a large share of positive reviews in the clinical literature. These findings sit well with our line of reasoning, in terms of the presumed informational and skill advantages associated with specialization. They are robust across concentration measures (see Tables 4 and 5), but do not hold for hypertension. This difference between the two therapeutic categories may be a finding of interest in itself, which deserves further scrutiny.

Another result of interest is that self-insured patients, and to a lesser extent Medicare patients, are prescribed cheaper hypertension drugs (the omitted categories is Private and/or HMO insurance). This finding implies that physicians may be indeed sensitive to the extent to which patients bear the costs of the treatment, and adjust their prescriptions accordingly. These results hold in hypertension when using either of the concentration measures, but it does not hold for depression; once again, this deserves further investigation.

Tables 4 and 5 show the results of the MNL using the γ^* and the γ indices respectively, and table 6 summarizes the results for the 3 measures. In general, the results are robust to the choice of concentration measure, with a stronger similarity between those for the Herfindahl and the γ^* indices, than between them and the γ. The only noticeable difference is that the interaction between advertising and concentration is positive and significant when using the Herfindahl or γ^*, but that is not the case when using γ. On the other hand, the statistical significance of concentration×price increases for γ vis a vis the other two measures. Thus, the Herfindahl and γ^* are somehow better able to pick up the

enhanced sensitivity of concentrated physicians to advertising, whereas the γ index is more able to pick up their enhanced sensitivity to price.

The fact that the Herfindahl and γ^* offer qualitatively the same results is very reassuring, implying that the estimation is not sensitive to the precise way of measuring concentration. In particular, the results are not simply resulting from differences across physicians in terms of the number of observed prescriptions. On the other hand, the differences between the results for these two indices and those for γ imply that the choice of *baseline* in measuring concentration may be consequential. Recall that the γ index is supposed to measure "excess concentration", that is, concentration above and beyond the average concentration implied by the market-wide shares. Thus, for this index to yield the observed statistical results, physician concentration must be specifically centered around drugs which embed high levels of low-cost information about drugs rather than simply being associated with drugs with high overall market shares. This is a much more stringent criterion (compared to concentration as measured by the Herfindahl or by γ^*), and hence we are not surprised that the results are weaker. However, as discussed in Section IV, the fact that the qualitative results hold even for γ (and increase in significance in terms of the price results) can be interpreted as a critical additional test that concentrated physicians are in fact sensitive to charactersitics associated with "cheap" information.

We have performed a large number of additional runs, varying the estimating equation along the following dimensions: (*i*) the set of variables included, both in terms of drug attributes and patient/physician characteristics; (*ii*) the "cut-off" point for including physicians in terms of the minimum number of observed number of prescriptions (i.e., we set the minimum cut-off at 3, 4, or 5 observed prescriptions); (*iii*) inclusion of drug attributes by themselves rather than drug fixed effects. The results are robust to these variations, with most of the differences being in the level of significance of the coefficients.[22] In general, the results for lagged market share are consistently stronger (and more robust) than for the other variables, whereas those for positive science are

more tenuous. As already mentioned, for virtually all specifications the results for depression are more consistent and significant than for hypertension.

VII. Counterfactuals: How Much Does Concentration Really Affect Drug Choice?

We highlight the quantitative significance of our results through a series of counterfactuals, shown in Table 7, which compare the probability of prescription of different types of drugs by physicians with different levels of concentration. For each characteristic, we divide the sample of drugs into two groups: HIGH and LOW (according to whether the drug has a value for that characteristic which is above or below the sample mean). As well, we divide the physicians into two groups according to whether they exhibit a HIGH or LOW level of concentration (once again, as compared to the sample mean). We then compare the mean predicted probabilities of physicians with High and Low concentration prescribing drugs of either type (according to the estimates using γ^* from Table 4).

For the antidepressant category, the differences between types are very large indeed. Highly concentrated physicians have a probability of prescribing a heavily advertised drug which is 36% higher than relatively unconcentrated doctors. As well, more highly concentrated physicians prescribe drugs with higher values of lagged market share with an 17% greater probability. While less striking, the results for the hypertension therapies are also significant. For example, the decline in the probability that a highly concentrated physician prescribes a less-advertised drug is of 10% (relative to the baseline probabilities associated with less concentrated prescribers). These results suggest that the statistically significant elements of our model are also quantitatively large, and hence that the covariation of concentration in prescribing and the type of drugs prescribed may be indeed an important empirical phenomena.

[22] The results are available from the authors by e-mail.

VIII. Concluding Remarks

The null hypothesis underlying our empirical inquiry is essentially that ***none*** of the interactions between drug characteristics and physician attributes should matter. Although one would expect that different physicians prescribe alternative drugs with different probabilities (after controlling for patient attributes), these differences should be in some sense random and not related to obvious, observable attributes of the physicians themselves. Such differences, if they exist, immediately evoke the possibility of systematic biases in their prescription behavior, biases that have a rather disturbing connotation. Thus, empirical findings to the effect that such systematic differences exist would be of interest in and of themselves. And indeed, one way to look at the results in this paper is that they uncover and quantify such differences, in a precise and coherent way.

However, the aim here is not just to establish and document a raw empirical fact. By focusing on concentration in prescribing as a key characteristic of physicians, we link these differences in prescription behavior to more fundamental but mostly unobservable features of physicians such as their diagnostic skill base. Furthermore, by looking at the interactions with certain drug characteristics such as advertising and previous market share, we relate the differences across physicians in their prescribing behavior to the "dearness" of the information conveyed, and its degree of generality (i.e. the extent to which it refers to the "average patient" rather than to the specificities of each patient). In so doing, we evoke a possible underlying agency problem, in terms of the informational investments that different physicians make in order to effectively match patients to drugs.

The results conform well with the hypothesized behavioral model: more concentrated physicians do tend to prescribe with higher probabilities drugs with higher previous market shares, and drugs that are heavily advertised (after controlling for the observed attributes of patients). There is some evidence also that they tend to prescribe with higher probabilities cheaper drugs, and drugs with higher shares of positive articles in the scientific literature. The results at least for previous market share and price persist even if

concentration is taken to mean "excess concentration." Thus, more concentrated physicians tend indeed to rely on "cheaper" sources of information, and may underinvest in the knowledge ingredients necessary for achieving a good match between patients and drugs.

There is potentially a whole range of policy implications stemming from the basic fact uncovered in this paper, namely the existence of an important source of variance in the prescription practices of physicians that evoke the possibility of systematic biases in their behavior. Thus, one can think of designing better incentives for physicians to acquire updated knowledge about drugs, investigate whether the time spent with each patient impacts the quality of the diagnosis (and hence the type of drugs prescribed), etc. There may be also practical implications for monitoring the behavior of physicians, which may be of help in the actual implementation of corrective policies. Suppose for example that a health organization (such as an HMO) wants to monitor the prescribing behavior of its physicians, precisely because it is concerned about possible biases in such behavior. At what sort of data or measures should it be looking at? What our results suggest is that concentration indices as used here may be a highly informative type of measure to monitor, since they constitute a window into more fundamental phenomena that are difficult to observe directly.

Further, our analysis of the role of the physician "filter" in the choice of drugs may contribute to the understanding of the diffusion of new pharmaceutical products. The diffusion of these products depends critically on the fact that physicians rather than patients have the authority to decide which drugs are to be used. To the extent physicians differ in their use of different types of information about drugs, then the diffusion path of a new drug will reflect the pattern of information generation and distribution by the innovating firm and the scientific and medical communities.

Finally, two methodological remarks: First, the link between concentration measures and the relative importance of "δ" versus "ε" in the context of discrete choice problems is a general one, and we hope that this understanding will find its way into similar issues in economics. Second, by mapping the geogrpahic concentration measures suggested by Ellison and Glaeser (1997) into our context, we provide further insight into the nature of these novel indices, highlight the importance of choosing a baseline appropriate to the economic question under consideration, and suggest that the scope of their possible application may be substantially broader than the geographic dispersion of indsutry.

BIBLIOGRAPHY

Aghion, P. and J. Tirole (1997). "Formal and Real Authority in Organizations," *Journal of Political Economy*, 105(1): 1-29.

Arrow, K. (1963). "Uncertainty and the Welfare Economics of Medical Care," *American Economic Review*, 53:941-73.

Berry, S. (1994). "Estimating Discrete Choice Models of Product Differentiation," *Rand Journal of Economics*, 25(2): 242-62.

Coscelli, A. (1998). "Entry of New Drugs and Doctors' Prescriptions," mimeo, University College London.

Drug Facts and Comparisons (1991), J.P. Lippincott Company, St. Louis (MO).

Drug Topics Red Book (various years) Medical Economics Company, Inc., Oradell (NJ).

FDA Orange Book (various years), Government Printing Office, Washington (DC).

Ellickson, P., S. Stern, and M. Trajtenberg (1998), "Patient Welfare and Patient Compliance: An Empirical Framework for Measuring the Benefits of Pharmaceutical Innovation," *Medical Care Output & Productivity*, forthcoming.

Ellison, G., and J. Chevalier (1997). "Risk-Taking by Mutual Fund Managers," *Journal of Political Economy* 105(6): 1167-1200.

Ellison, G. and E. Glaeser (1997). "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach," *Journal of Political Economy*, 105(5): 889-927.

Ellison, S., I. Cockburn, Z. Griliches, and J. Hausman (1997), "Characteristics of the Demand for Pharmaceutical Products: An Examination of Four Cephalosporins," *RAND Journal of Economics*, 28(3): 426-46.

Gruber, J. and M. Owings (1996). " Physician Incentives and Cesarean Delivery," *RAND Journal of Economics* 27(1): 99-123.

Hellerstein, J. (1998), "The Importance of the Physician in the Generic versus Trade-Name Decision," *RAND Journal of Economics*, 29(1): 108-36.

Hubbard, T. (1998), "An Empirical Investigation of Moral Hazard in the Motor Vehicle Inspection Market," *RAND Journal of Economics* 29(2): 406-26.

IMS, International (various years), *Journal, Mail and Detailing Audit.*

McGuire, T. and M. Pauly (1991). "Physician Response to Fee Changes with Multiple Payers," *Journal of Health Economics* 10: 385-410.

National Ambulatory Medical Care Survey (various years). National Center for Health Care Statistics, Washington (DC).

Physician's Desk Reference (1992) Medical Economics Company, Inc., Oradell (NJ).

Weisbrod, B. (1991). "The Health Care Quadrilemma: An Essay on Technological Change, Insurance, Quality of Care, and Cost Containment," *Journal of Economic Literature*, 29:523-52.

Figure A
Unobserved Heterogeneity, Concentration, and Type of Drugs Prescribed

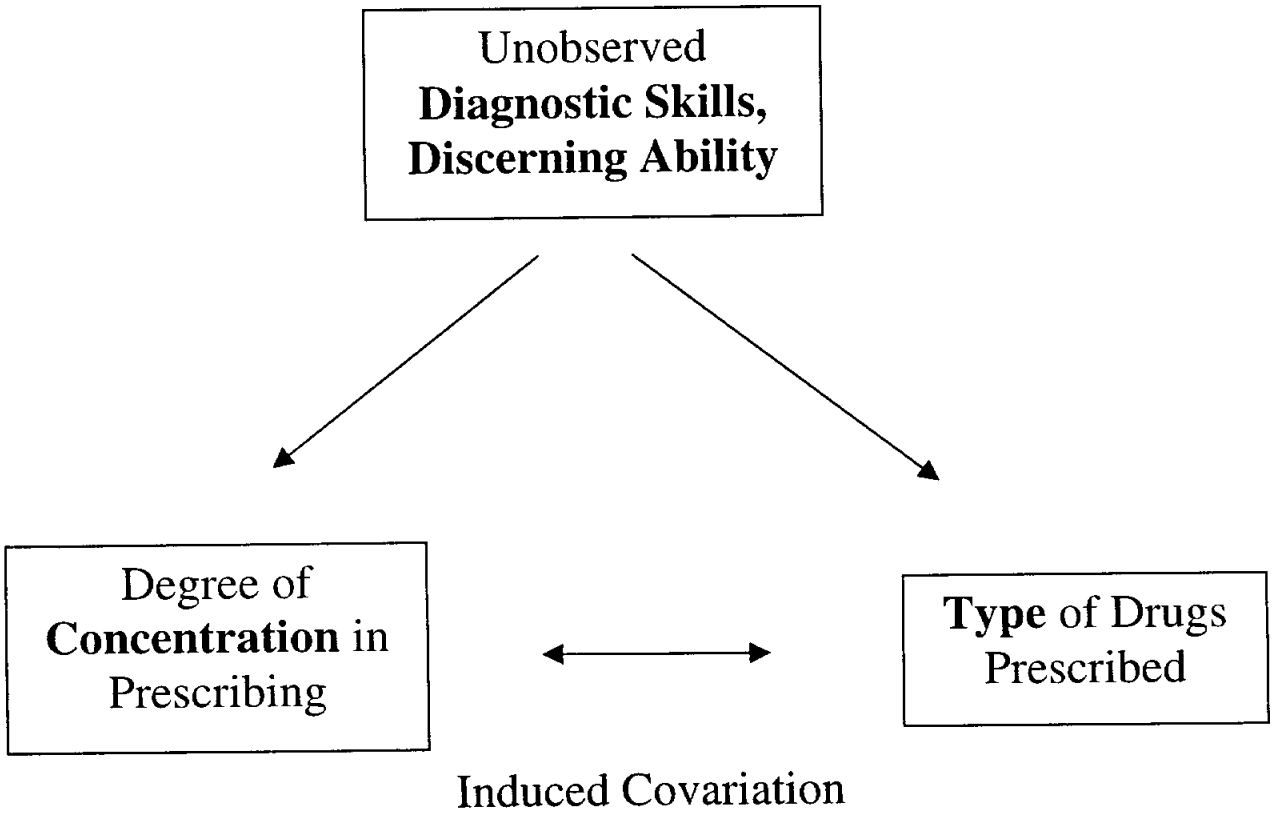
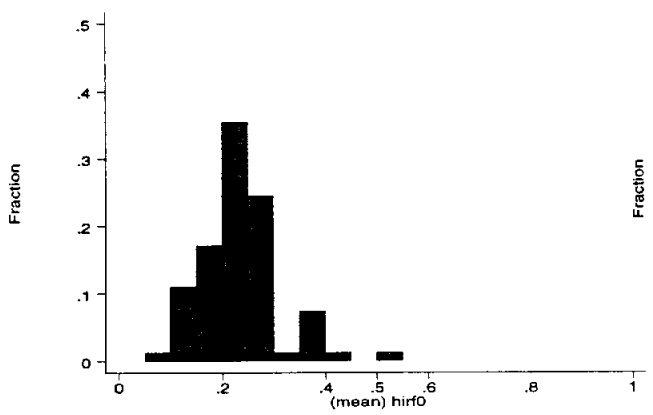
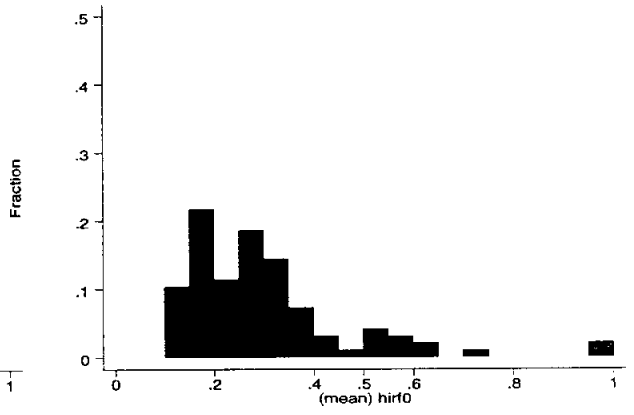


FIGURE B
DISTRIBUTION OF CONCENTRATION MEASURES

HERFINDAHL

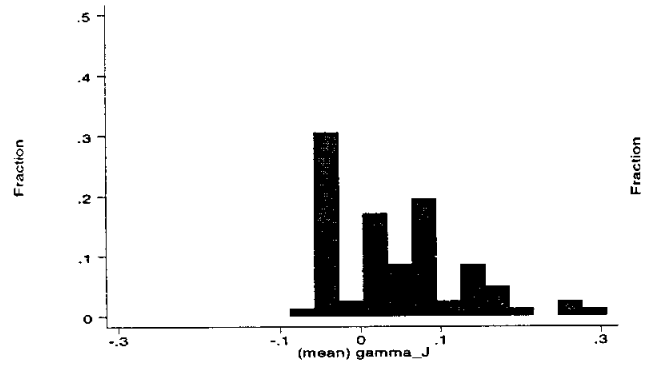


HYPERTENSION

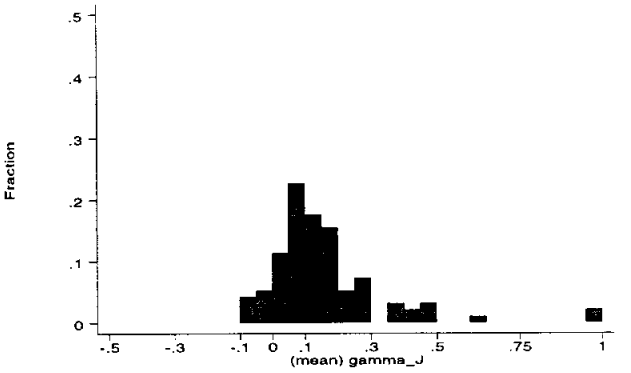


DEPRESSION

γ^*

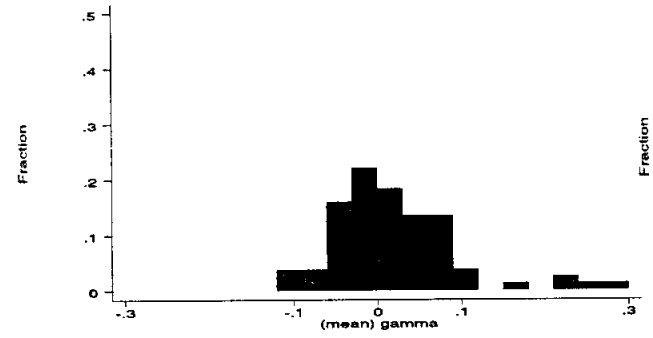


HYPERTENSION

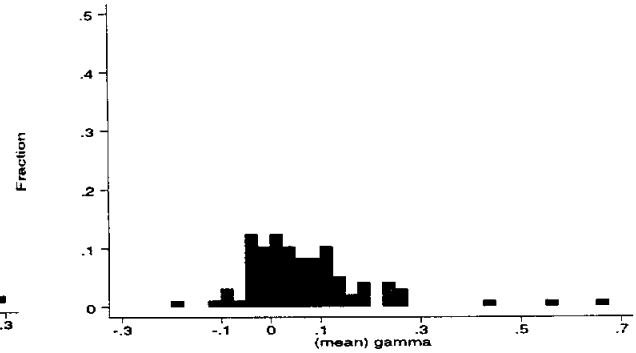


DEPRESSION

γ



HYPERTENSION

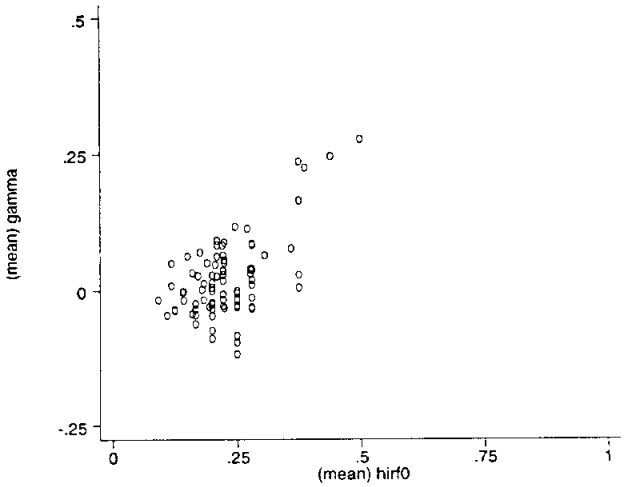


DEPRESSION

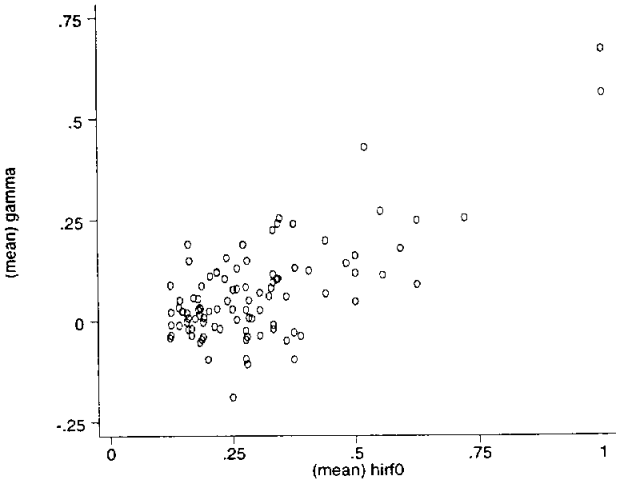
FIGURE C

PAIRWISE CORRELATION OF CONCENTRATION MEASURES

γ ON HERFINDHAHL

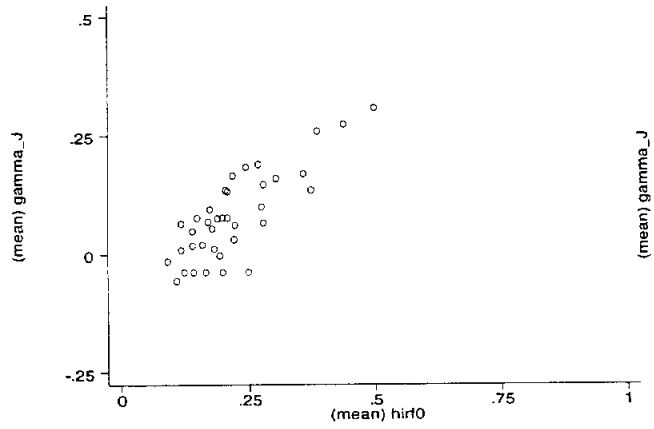


HYPERTENSION

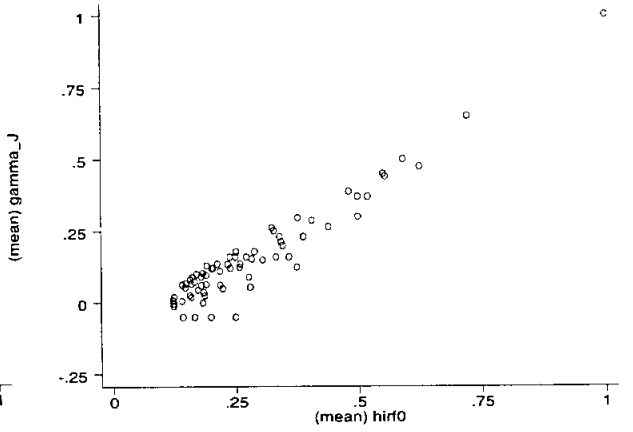


DEPRESSION

γ^* ON HERFINDHAHL



HYPERTENSION



DEPRESSION

TABLE 1
SUMMARY STATISTICS

DEFINITION	SOURCE	VARIABLE NAME	DEPRESSION		HYPERTENSION	
			MEAN	STD. DEV.	MEAN	STD. DEV.
PHYSICIAN ATTRIBUTES						
Specialist	NAMCS	Specialist	0.94	0.24	0.18	.39
Number of Observed Prescriptions	NAMCS	# of RX	10.85	7.25	8.24	6.44
Herfindahl Index	NAMCS	Herfindhal	0.30	0.16	0.23	0.07
γ (see text)	NAMCS	γ	0.07	0.13	0.02	0.07
γ^* (see text)	NAMCS	γ^*	0.15	0.18	0.05	0.08
Number of Physicians			97		82	
DRUG CHARACTERISTICS						
1991 Market Share (%)	1991 NAMCS	Market Share	0.04	0.04	0.025	0.29
Advertising/Promotion Expenditures ($000s)	IMS Journal, Mail,Detailing Audit	Advertising	28.16	42.07	33.82	37.47
Avg. Branded Price ($)	RED BOOK	Price	3.54	3.61	2.70	2.46
Share of Clinical Articles w/ Positive Recs (%)	MEDLINE	Positive Science	0.42	0.24	0.51	0.17
Number of Drugs			20		27	
PATIENT ATTRIBUTES						
Age	NAMCS	Age	43.86	14.89	63.48	15.31
Male	NAMCS	Male	0.32	0.47	0.39	0.49
Black	NAMCS	Black	0.03	0.18	0.15	0.36
Number of Patients		N	1015		552	
PATIENT INSURANCE STATUS						
Self-Insured	NAMCS	Self-Insured	0.23	0.42	0.10	0.30
HMO	NAMCS	HMO	0.17	0.38	0.16	0.37
Medicare	NAMCS	Medicare	0.14	0.34	0.50	0.50

TABLE 2
AVERAGE DRUG CHARACTERISTICS
CONDITIONAL ON HERFINDHAL RANGE

DEPRESSION

	"LOW" HERF MD's	"HIGH" HERF MD's
Market Share 1991	0.07	0.10
Advertising	39.89	62.20
Price	3.54	2.98
Positive Science	0.47	0.50

HYPERTENSION

	"LOW" HERF MD's	"HIGH" HERF MD's
Market Share 1991	0.04	0.05
Advertising	42.17	56.88
Price	2.43	2.30
Positive Science	0.49	0.50

TABLE 3A
MULTINOMIAL LOGIT
"HERFINDAHL" CONCENTRATION MEASURE

THERAPEUTIC CATEGORY = DEPRESSION

	Market Share 1991	Advertising	Price	Positive Science
Drug Fixed Effects	**Significant**			
PHYSICIAN ATTRIBUTES				
Herfindahl	**23.219** **(5.425)**	**0.027** **(0.008)**	-0.027 (0.166)	2.375 (2.155)
# of RX	0.006 (0.067)	**2.03 E-04** **(0.90 E-04)**	0.001 (0.002)	**0.051** **(0.026)**
Specialist	3.454 (3.000)	**-0.017** **(0.005)**	0.002 (0.068)	**3.639** **(1.480)**
PATIENT INSURANCE STATUS				
Self-Insured	0.571 (1.327)	0.001 (0.002)	-0.040 (0.035)	-0.559 (0.482)
Medicare	0.218 (2.215)	**-0.007** **(0.003)**	0.014 (0.038)	0.299 (0.592)
PATIENT ATTRIBUTES				
Age	-0.023 (0.043)	**-1.46 E-04** **(0.58 E-04)**	**-0.002** **(0.001)**	-0.011 (0.014)
Male	-0.748 (1.217)	-4.89 E-04 (0.002)	-0.061 (0.029)	-0.605 (0.410)
Black	-3.038 (3.020)	0.003 (0.004)	0.065 (0.056)	-0.981 (1.057)
# of Observations:	**1015**			
Log-Likelihood:	**-2400.571**			

TABLE 3B
MULTINOMIAL LOGIT
"HERFINDAHL" CONCENTRATION MEASURE

THERAPEUTIC CATEGORY = HYPERTENSION

	Market Share 1991	**Advertising**	**Price**	**Positive Science**
Drug Fixed Effects	**Significant**			
PHYSICIAN ATTRIBUTES				
Herfindahl	**43.099** **(19.547)**	**0.030** **(0.014)**	-0.661 (0.417)	4.601 (4.218)
# of RX	**0.340** **(0.126)**	3.15 E-05 (9.83 E-05)	-0.003 (0.003)	0.017 (0.032)
Specialist	-3.672 (3.306)	0.003 (0.002)	-0.059 (0.065)	-0.657 (0.731)
PATIENT INSURANCE STATUS				
Self-Insured	**8.743** **(4.485)**	0.001 (0.003)	**-0.313** **(0.112)**	0.989 (0.985)
Medicare	2.947 (3.277)	4.47 E-05 (0.002)	**-0.113** **(0.064)**	0.802 (0.794)
PATIENT ATTRIBUTES				
Age	0.087 (0.105)	-3.97 E0-05 (7.95 E-05)	-0.002 (0.002)	**-0.060** **(0.026)**
Male	**4.878** **(2.579)**	-0.001 (0.002)	-0.045 (0.052)	0.614 (0.612)
Black	1.045 (3.611)	-1.83 E-04 (0.003)	-0.089 (0.074)	0.289 (0.885)
# of Observations:	**552**			
Log-Likelihood:	**-1592.785**			

TABLE 4
γ^* CONCENTRATION MEASURE

THERAPEUTIC CATEGORY = DEPRESSION

	Market Share 1991	Advertising	Price	Positive Science
Drug Fixed Effects	**Significant**			
PHYSICIAN ATTRIBUTES				
γ^*	**28.066** **(4.981)**	**0.014** **(0.007)**	0.005 (0.159)	**10.786** **(1.857)**
Specialist	-1.792 (3.076)	**-0.010** **(0.005)**	-0.008 (0.072)	1.706 (1.510)
PATIENT INSURANCE STATUS				
Self-Insured	0.106 (1.333)	0.001 (0.002)	-0.042 (0.035)	**-1.011** **(0.484)**
Medicare	0.319 (2.240)	**-0.007** **(0.003)**	0.019 (0.038)	0.428 (0.605)
PATIENT ATTRIBUTES	**INCLUDED**			
# of Observations:	**1015**			
Log-Likelihood:	**-2382.789**			

THERAPEUTIC CATEGORY = HYPERTENSION

	Market Share 1991	Advertising	Price	Positive Science
Drug Fixed Effects	**Significant**			
PHYSICIAN ATTRIBUTES				
γ^*	**59.073** **(16.947)**	**0.023** **(0.011)**	-0.424 (0.355)	1.184 (3.660)
Specialist	-3.973 (3.329)	0.002 (0.002)	-0.058 (0.066)	-0.661 (0.722)
PATIENT INSURANCE STATUS				
Self-Insured	**8.445** **(4.497)**	8.51 E-04 (0.003)	**-0.321** **(0.111)**	0.916 (0.965)
Medicare	3.533 (3.293)	2.10 E-04 (0.002)	**-0.117** **(0.065)**	0.755 (0.788)
PATIENT ATTRIBUTES	**INCLUDED**			
# of Observations:	**552**			
Log-Likelihood:	**-1593.533**			

TABLE 5
γ CONCENTRATION MEASURE

THERAPEUTIC CATEGORY = DEPRESSION

	Market Share 1991	Advertising	Price	Positive Science
Drug Fixed Effects	**Significant**			
PHYSICIAN ATTRIBUTES				
γ	**17.436** **(6.389)**	-0.005 (0.009)	**-0.351** **(0.169)**	-1.331 (2.207)
Specialist	0.832 (2.912)	**-0.017** **(0.005)**	0.033 (0.067)	**4.189** **(1.445)**
PATIENT INSURANCE STATUS				
Self-Insured	1.137 (1.291)	0.001 (0.002)	-0.036 (0.035)	-0.625 (0.470)
Medicare	-0.220 (2.178)	**-0.007** **(0.003)**	0.021 (0.038)	0.322 (0.591)
PATIENT ATTRIBUTES	**INCLUDED**			
# of Observations:	**1015**			
Log-Likelihood:	**-2438.742**			

THERAPEUTIC CATEGORY = HYPERTENSION

	Market Share 1991	Advertising	Price	Positive Science
Drug Fixed Effects	**Significant**			
PHYSICIAN ATTRIBUTES				
γ	**32.518** **(19.825)**	-0.002 (0.014)	-0.528 (0.411)	6.854 (4.333)
Specialist	-3.147 (3.280)	0.003 (0.002)	-0.060 (0.066)	-0.747 (0.717)
PATIENT INSURANCE STATUS				
Self-Insured	**8.333** **(4.462)**	6.73 E-04 (0.003)	**-0.319** **(0.111)**	1.002 (0.966)
Medicare	3.155 (3.264)	2.84 E-04 (0.002)	**-0.114** **(0.065)**	0.887 (0.788)
PATIENT ATTRIBUTES	**INCLUDED**			
# of Observations:	**552**			
Log-Likelihood:	**-1599.327**			

TABLE 6
CONCENTRATION RESULTS SUMMARY

THERAPEUTIC CATEGORY = DEPRESSION

	Market Share 1991	Advertising	Price	Positive Science
HERF	+	+	-	+
γ^*	+	+	+	+
γ	+	-	-	-

THERAPEUTIC CATEGORY = HYPERTENSION

	Market Share 1991	Advertising	Price	Positive Science
HERF	+	+	-	+
γ^*	+	+	-	+
γ	+	-	-	+

TABLE 7
DIFFERENCES IN PROBABILITY OF PRESCRIBING DIFFERENT TYPES OF DRUGS BASED ON LEVEL OF γ^* (COUNTERFACTUALS)

THERAPEUTIC CATEGORY = DEPRESSION

		Avg. Prescription Probability for "LOW" γ^* MDs	Avg. Prescription Probability for "HI" γ^* MD's	Percentage Difference for "HI" γ^*
Market Share 1991	LOW	0.030	0.022	-26.7%
	HIGH	0.086	0.101	17.4
Advertising	LOW	0.043	0.031	-27.9
	HIGH	0.063	0.086	36.5
Price	LOW	0.048	0.053	10.4
	HIGH	0.057	0.041	-28.1
Positive Science	LOW	0.032	0.026	-18.7
	HIGH	0.069	0.074	7.2

THERAPEUTIC CATEGORY = HYPERTENSION

		Avg. Prescription Probability for "LOW" γ^* MD's	Avg. Prescription Probability for "HI" γ^* MD's	Percentage Difference for "HI" γ^*
Market Share 1991	LOW	0.018	0.015	-16.7%
	HIGH	0.070	0.073	4.2
Advertising	LOW	0.038	0.034	-10.5
	HIGH	0.036	0.039	8.3
Price	LOW	0.037	0.039	5.4
	HIGH	0.036	0.032	-11.1
Positive Science	LOW	0.042	0.044	4.7
	HIGH	0.030	0.029	-3.3

APPENDIX A

Proof of Proposition 1

Consider $H_l = \sum_{j=1}^{J} s_{lj}^2$ and $E(\delta_j)_l = \sum_{j=1}^{J} s_{lj}\delta_j$. We need to show that $\frac{\partial H_l}{\partial \theta} > 0$ and $\frac{\partial E(\delta_j)_l}{\partial \theta} > 0$. Note that $\frac{\partial H_l}{\partial \theta} = 2\sum_{j=1}^{J} s_{lj}\frac{\partial s_{lj}}{\partial \theta}$ and $\frac{\partial E(\delta_j)_l}{\partial \theta} = \sum_{j=1}^{J}\delta_j\frac{\partial s_{lj}}{\partial \theta}$. As well, $\sum_{j=1}^{J}\frac{\partial s_{lj}}{\partial \theta} = 0$ since $\sum_{j=1}^{J} s_{lj} = 1$. In the case of the multinomial logit, $s_{lj} = \frac{e^{\theta_l\delta_j}}{\sum_{k\in K} e^{\theta_l\delta_k}}$, which implies that (a) if $s_{lj} > s_{lk} \Leftrightarrow \delta_{lj} > \delta_{lk}$ and (b) $\frac{\partial s_{lj}}{\partial \theta} = s_{lj}(\delta_j - \frac{\sum_{k\in K}\delta_k e^{\theta_l\delta_k}}{\sum_{k\in K} e^{\theta_l\delta_k}})$. If $\delta_j > \frac{\sum_{k\in K}\delta_k e^{\theta_l\delta_k}}{\sum_{k\in K} e^{\theta_l\delta_k}}$, then $\frac{\partial s_{lj}}{\partial \theta_l} > 0$ (and conversely for $\delta_j < \frac{\sum_{k\in K}\delta_k e^{\theta_l\delta_k}}{\sum_{k\in K} e^{\theta_l\delta_k}}$). Denote $A = \left\{ j \,\middle|\, \delta_j > \frac{\sum_{k\in K}\delta_k e^{\theta_l\delta_k}}{\sum_{k\in K} e^{\theta_l\delta_k}} \right\}$, the set of drugs for which $\frac{\partial s_{lj}}{\partial \theta} > 0$ and $B = \left\{ j \,\middle|\, \delta_j < \frac{\sum_{k\in K}\delta_k e^{\theta_l\delta_k}}{\sum_{k\in K} e^{\theta_l\delta_k}} \right\}$.

Note that since $\sum_{j\in J}\frac{\partial s_{lj}}{\partial \theta} = 0, \sum_{j\in A}\frac{\partial s_{lj}}{\partial \theta} = -\sum_{j\in B}\frac{\partial s_{lj}}{\partial \theta}$. To show that $\sum_{j\in J} s_j\frac{\partial s_{lj}}{\partial \theta} > 0$, it suffices to show that $\sum_{j\in A} s_j\frac{\partial s_{lj}}{\partial \theta} > \left|\sum_{j\in B} s_j\frac{\partial s_{lj}}{\partial \theta}\right|$, since all negative elements of the sum are included in B.

We show this inequality by by noting that $\sum_{j\in A} s_j\frac{\partial s_{lj}}{\partial \theta} > \min_{j\in A}(s_j)\sum_{j\in A}\frac{\partial s_{lj}}{\partial \theta}$ and $\left|\sum_{j\in B} s_j\frac{\partial s_{lj}}{\partial \theta}\right| < \max_{j\in B}(s_j)\left|\sum_{j\in B}\frac{\partial s_{lj}}{\partial \theta}\right|$ and that $\min_{j\in A}(s_j) > \max_{j\in B}(s_j)$ by (b) above.

Consequently, $\sum_{j\in A} s_j\frac{\partial s_{lj}}{\partial \theta} > \min_{j\in A}(s_j)\sum_{j\in A}\frac{\partial s_{lj}}{\partial \theta} > \max_{j\in B}(s_j)\left|\sum_{j\in B}\frac{\partial s_{lj}}{\partial \theta}\right| > \left|\sum_{j\in B} s_j\frac{\partial s_{lj}}{\partial \theta}\right|$, which is what we wanted to prove.

The same argument applies for $E(\delta_j)_l$ by replacing s_{lj} with δ_j in the weighted sums. The derivative with respect to γ^* follows from the fact that this is simply a linear function of H_l.

APPENDIX B.1
MULTINOMIAL LOGIT
"HERFINDAHL" CONCENTRATION MEASURE

THERAPEUTIC CATEGORY = DEPRESSION

	Market Share 1991	Advertising	Price	Positive Science
Drug Fixed Effects	**Significant**			
PHYSICIAN ATTRIBUTES				
Herfindahl	25.561 (6.121)	0.022 (0.009)	-0.138 (0.176)	2.470 (2.329)
# of RX	0.026 (0.078)	1.34 E-04 (1.06 E-04)	-0.001 (0.002)	0.040 (0.028)
Specialist	2.618 (3.213)	-0.015 (0.006)	-0.004 (0.071)	3.425 (1.508)
MSA	1.157 (1.391)	7.63 E-07 (1.91 E-06)	0.022 (0.032)	-0.383 (0.468)
PATIENT INSURANCE STATUS				
HMO	-2.521 (2.486)	2.83 E-06 (3.35 E-06)	0.113 (0.062)	0.123 (0.894)
Medicare	-1.472 (2.589)	-0.003 (0.004)	0.052 (0.047)	0.620 (0.704)
Self-Pay	0.623 (2.338)	0.002 (0.003)	0.042 (0.055)	-0.109 (0.747)
PATIENT DEMOGRAPHICS				
Age	-0.050 (0.052)	-1.58 E-04 (6.98 E-05)	-0.002 (0.001)	-0.017 (0.017)
Male	-0.686 (1.340)	-3.68 E-04 (0.002)	-0.043 (0.033)	-0.418 (0.456)
Black	-2.549 (3.094)	0.003 (0.004)	0.105 (0.060)	-0.940 (1.099)
CHARACTERISTICS OF VISIT				
Duration	-0.005 (0.046)	4.21 E-08 (6.30 E-08)	-0.001 (0.001)	0.011 (0.015)
New Patient	-1.763 (2.806)	2.13 E-06 (3.73 E-06)	0.056 (0.066)	0.749 (0.938)
AVERAGE PATIENT INSURANCE STATUS				
% HMO	4.187 (3.305)	-1.71 E-06 (4.54 E-06)	-0.066 (0.083)	0.698 (1.214)
% Medicare	10.340 (5.163)	1.80 E-05 (7.32 E-06)	-0.074 (0.103)	-1.989 (1.544)
% Self-Pay	-1.035 (3.003)	-7.05 E-07 (4.12 E-06)	-0.196 (0.077)	0.796 (1.005)
AVERAGE PATIENT DEMOGRAPHICS				
Average Age	0.060 (0.096)	8.54 E-09 (1.37 E-07)	5.11 E-04 (0.002)	0.045 (0.035)
% Male	0.073 (3.346)	-3.68 E-04 (0.002)	-0.122 (0.080)	-1.489 (1.129)
AVERAGE CHARACTERISTICS OF VISIT				
Average Duration	0.122 (0.074)	-1.03 E-07 (1.02 E-07)	0.006 (0.002)	0.003 (0.025)
Average New Patient	0.588 (3.772)	-1.27 E-06 (5.10 E-06)	-0.323 (0.110)	0.044 (1.219)
# of Observations:	**1015**			
Log-Likelihood:	**-2366.038**			

APPENDIX B.2
MULTINOMIAL LOGIT
"HERFINDAHL" CONCENTRATION MEASURE

THERAPEUTIC CATEGORY = HYPERTENSION

	Market Share 1991	Advertising	Price	Positive Science
Drug Fixed Effects	**Significant**			
PHYSICIAN ATTRIBUTES				
Herfindahl	51.207 (20.309)	0.031 (0.015)	-0.581 (0.422)	5.750 (4.315)
# of RX	0.366 (0.137)	4.25 E-05 (1.06 E-04)	-0.004 (0.003)	0.016 (0.035)
Specialist	-3.063 (3.548)	0.004 (0.002)	-0.042 (0.069)	-0.028 (0.785)
MSA	0.811 (3.060)	-2.29 E-06 (2.25 E-06)	-0.004 (0.062)	0.281 (0.723)
PATIENT INSURANCE STATUS				
HMO	-8.875 (6.098)	-3.02 E-06 (4.74 E-06)	-0.072 (0.114)	-0.478 (1.477)
Medicare	1.715 (4.279)	-0.004 (0.003)	-0.181 (0.086)	-0.612 (1.011)
Self-Pay	4.600 (6.045)	-5.16 E-04 (0.004)	-0.279 (0.137)	-0.203 (1.305)
PATIENT DEMOGRAPHICS				
Age	0.021 (0.129)	4.27 E-06 (9.93 E-05)	-0.002 (0.002)	-0.030 (0.032)
Male	4.882 (3.034)	-0.002 (0.002)	-0.011 (0.058)	0.913 (0.722)
Black	0.393 (3.691)	-5.12 E-05 (0.003)	-0.079 (0.076)	0.458 (0.913)
CHARACTERISTICS OF VISIT				
Duration	-0.031 (0.199)	-5.58 E-08 (1.57 E-07)	-0.002 (0.004)	-0.065 (0.047)
New Patient	-10.180 (8.671)	1.29 E-06 (5.62 E-06)	0.037 (0.166)	0.979 (1.646)
AVERAGE PATIENT INSURANCE STATUS				
% HMO	15.378 (8.112)	-4.21 E-06 (6.51 E-06)	-0.071 (0.155)	-0.505 (1.989)
% Medicare	4.477 (7.616)	8.69 E-06 (5.84 E-06)	0.124 (0.144)	4.550 (1.875)
% Self-Pay	10.882 (9.279)	4.04 E-08 (6.50 E-06)	-0.143 (0.191)	2.423 (2.046)
AVERAGE PATIENT DEMOGRAPHICS				
Average Age	0.086 (0.222)	-1.84 E-07 (1.74 E-07)	-0.003 (0.004)	-0.123 (0.059)
% Male	4.254 (6.204)	5.14 E-04 (4.51 E-04)	-0.069 (0.124)	-0.871 (1.428)
AVERAGE CHARACTERISTICS OF VISIT				
Average Duration	0.247 (0.285)	2.05 E-07 (2.20 E-07)	0.009 (0.005)	0.103 (0.067)
Average New Patient	-11.869 (13.634)	-5.60 E-06 (9.10 E-06)	-0.363 (0.259)	-2.728 (2.662)
# of Observations:	**522**			
Log-Likelihood:	**-1568.877**			