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The Diversity of Concentrated Prescribing Behavior: An Application to Antipsychotics
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ABSTRACT

Physicians prescribing drugs for patients with schizophrenia and related conditions are remarkably concentrated in their choice among antipsychotic drugs. In 2007 the single antipsychotic drug prescribed by a physician accounted for 66% of all antipsychotic prescriptions written by that physician. Which particular branded antipsychotic was the prescriber's "favorite" varied widely across physicians, i.e. physician prescribing concentration patterns are diverse. Building on Frank and Zeckhauser's [2007] characterization of physician treatments varying from "custom made" to "ready-to-wear", we construct a model of physician learning that generates a number of hypotheses. Using 2007 annual antipsychotic prescribing behavior on 17,652 physicians from IMS Health, we evaluate these predictions empirically. While physician prescribing behavior is generally quite concentrated, prescribers having greater volumes, those with training in psychiatry, male prescribers, and those not approaching retirement age tend to have less concentrated prescribing patterns.

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I. INTRODUCTION

Consider a physician seeing a patient with a confirmed diagnosis for which a number of alternative pharmaceutical treatments are available. Patient response to the various treatments is idiosyncratic and unpredictable in terms of both efficacy and side effects, and there is little clinical evidentiary literature upon which the physician can base an *ex ante* choice among the alternative drug treatments. What treatment algorithms might the physician employ to gather evidence and learn regarding the efficacy and tolerability of the variety of possible drug therapies for the patient?

Given this uncertainty and imperfect information, one possibility is for the physician to concentrate prescribing behavior on a single drug. In this way the physician engages in learning by doing, observes responses to that drug, adjusts dosage strength as warranted, and thereby exploits his/her accumulating knowledge and experience. Simultaneously the physician could also counsel the patient on the efficacy and side effect responses he/she might experience, thereby improving patient adherence and outcomes, and engaging the patient to help maintain symptom remission.

Alternatively, the physician might diversify prescribing across several drugs in an attempt to personalize the treatment and find the best match between the patient and the drug. Specifically, based on information from the patient's history, limited experience with several other drugs, the existing scientific and clinical literature, conversations with fellow medical professionals in the local and larger geographical community, and perhaps interactions with pharmaceutical sales representatives, the physician might select the therapy that *a priori* appears to be the best match with the particular patient's characteristics.

The physician can learn from either exploiting or exploring, concentrating or diversifying, prescribing "ready-to-wear"vs. "custom-made" treatments.[1] Physicians continually face this tradeoff as they treat patients and invest in learning about available treatments. How does the choice along this treatment diversity continuum vary by the physician's specialty, volume of patients treated, age and

training? If physicians concentrate their prescribing, is there a convergence and relative unanimity on their choice of a favorite drug, or is concentration non-uniform? Are there persistent geographic differences in physician prescribing behavior? If the set of prescribed drugs is diverse, do the physician's drug utilization shares mimic regional or national shares? These are the issues we address in this research, with an application to a particular therapeutic class of drugs known as antipsychotics. The issues are important, for understanding how physicians respond to new product launches, novel scientific and comparative effectiveness information, their own experience, and safety messages from the U.S. Food and Drug Administration is critical to managing the diffusion of medical information, and has significant clinical adoption and public health implications as well.

That physician prescribing behavior is relatively concentrated has been documented by, among others, Frank and Zeckhauser [2007].[2] They report that among 1372 primary care physicians surveyed in 2004, the fraction of prescriptions accounted for by the most prescribed medication used by the physician was generally quite high across four acute and five chronic conditions (averaging 60%), but was about 13 percentage points lower for chronic than acute conditions. More generally, while in some cases patient demographic factors affected physician treatment variability, patient clinical factors played a startlingly minor role. Physician "read-to-wear" treatment norms in some cases could be perceived as "as sensible response to complex decision-making", but in other cases could be viewed as "disturbing" and "based on idiosyncratic physician-specific preferences or severe biases in the application of heuristics."[3] Our research extends their analysis in several ways.[4] We focus on antipsychotics -- medicines treating primarily chronic conditions, and examine prescriber behavior across a much larger number and variety of specialties. We also put forward a theoretical framework based on the Bayesian learning model that enables us to construct and examine several additional hypotheses empirically. However, unlike Frank and Zeckhauser, we only observe physicians, and not the patients they treat.

We proceed as follows. We first provide a brief background on several generations of antipsychotic drugs and the illnesses they treat. We then report preliminary evidence on concentrated vs. diversified prescribing behavior, and utilize our initial findings on "diverse concentration" to put forward a theoretical framework that enables us to construct several hypotheses. After discussing the data and econometric framework, we present a substantial set of empirical findings. We conclude by relating our findings to the geographical variation literature, and suggest directions for future research.

II. ANTIPSYCHOTICS FOR THE TREATMENT OF SCHIZOPHRENIA AND RELATED CONDITIONS

Schizophrenia is an incurable mental illness. It is characterized by "gross distortions of reality, disturbances of language and communications, withdrawal from social interaction, and disorganization and fragmentation of thought, perception and emotional reaction".[5] Symptoms are both positive (hallucinations, delusions, voices) and negative (depression, lack of emotion). The prevalence of schizophrenia is 1-2%, with genetic factors at play but otherwise unknown etiology. The illness tends to strike males in late teens and early twenties, and females five or so years later. As the illness continues, persons with schizophrenia frequently experience unemployment, lose contact with their family, and become homeless; a substantial proportion experience periods of incarceration.[6]

Because schizophrenia is a chronic illness affecting virtually all aspects of life of affected persons, the goals of treatment are to reduce or eliminate symptoms, maximize quality of life and adaptive functioning, and to promote and maintain recovery from the adverse effects of illness to the maximum extent possible.[7] In the US, Medicaid is the largest payer of medical and drug benefits to people with schizophrenia.[8]

From 1955 up through the early 1990s, the mainstays of pharmacological treatment of schizophrenia were *conventional* or *typical* antipsychotic (also called *neuroleptic*) drugs that were more effective in treating the positive than the negative symptoms, but frequently resulted in extrapyramidal side effects such as tardive dyskinesia (an involuntary movement disorder most often characterized by

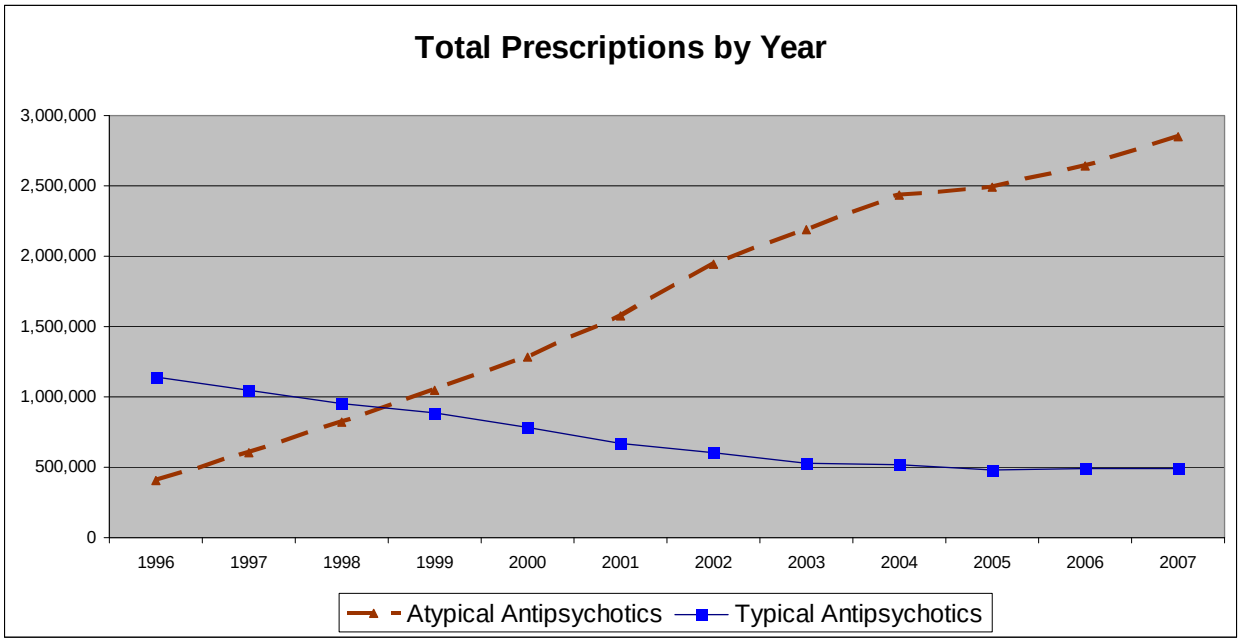
puckering of the lips and tongue, or writhing of the arms or legs), that may persist even after the drug is discontinued, and for which currently there is no effective treatment. In 1989, Clozaril (generic name clozapine) was introduced into the U.S. as the first in a new therapeutic class of drugs called *atypical* antipsychotics; this drug has also been dubbed a first generation atypical (FGA). Although judged by many still to be the most effective among all antipsychotic drugs, for 1-2% of individuals taking clozapine a potentially fatal condition called agranulocytosis occurs (drop in the white blood cell count, leaving the immune system potentially compromised). Patients taking clozapine must therefore have their white blood cell count measured by a laboratory test on a regular basis, and satisfactory laboratory test results must be communicated to the pharmacist before a prescription can be dispensed. For this reason, currently clozapine is generally used only for individuals who do not respond to other antipsychotic treatments.[9]

Between 1993 and 2002, five so-called second generation atypical ("SGA") antipsychotic molecules were approved by the FDA and launched in the US, including Risperdal (risperidone, 1993), Zyprexa (olanzapine, 1996), Seroquel (quetiapine, 1997), Geodon (ziprasidone, 2001) and Abilify (aripiprazole, 2002). Guidelines from the American Psychiatric Association state that although each of these five second generation atypicals is approved for the treatment of schizophrenia (some later also received FDA approval for treatment of bipolar disease, major depressive disorder, as well as various pediatric/adolescent patient subpopulation approvals), they also note that "In addition to having therapeutic effects, both first- and second-generation antipsychotic agents can cause a broad spectrum of side effects. Side effects are a crucial aspect of treatment because they often determine medication choice and are a primary reason for medication discontinuation."[10]

Initially these SGAs were perceived as having similar efficacy for positive symptoms and superior efficacy for negative symptoms relative to FGAs, but without the FGA extrapyramidal and agranulocytosis side effects. However, beginning in about 2001-2002 and continuing to the present, a

literature has developed regarding the association of SGAs with weight gain and the onset of diabetes, along with related metabolic syndrome side effects, particularly associated with the use of Zyprexa and clozapine and less so for Risperdal. Various professional treatment guidelines have counseled close scrutiny of individuals prescribed Zyprexa, clozapine and Risperdal. The FDA has ordered manufacturers to add bolded and boxed warnings to the product labels, initially for all atypicals, and later, to both typical and atypical antipsychotic labels. The labels have been augmented further with warnings regarding antipsychotic treatment of elderly patients having dementia, since this subpopulation appears to be at greater risk for stroke and death.[11]

Figure 1: Number of Typical and Atypical Prescriptions, annually 1996-2007.



Source: Authors' calculations based on IMS Health Incorporated Xponent™ 1996-2007 data.

Despite this controversy, as seen in Figure 1, based on a 10% random sample of all antipsychotic prescribers in the U.S. (more data details below), the number of atypical antipsychotic prescriptions dispensed between 1996 and 2007 increased about sevenfold from about 400,000 in 1996 to 2,800,000 in 2007, even as the number of conventional or typical antipsychotic prescriptions fell 45% from 1,100,000 in 1996 to about 500,000 in 2003, and has stabilized at that level since then.[12] As a share of

all antipsychotic prescriptions, the atypical share more than tripled from about 27% in 1996 to 85% in 2007. It is also noteworthy that despite all the concerns about the safety and efficacy of antipsychotics, the total number of antipsychotic prescriptions dispensed in this 10% random sample – typical plus atypical – more than doubled between 1996 and 2007, from about 1,500,000 to about 3,300,000, an average annual growth rate (AAGR) of 7.4%.

III. PRELIMINARY EVIDENCE ON CONCENTRATED VS. DIVERSIFIED PRESCRIBING BEHAVIOR

Although manufacturers received approval to market reformulated versions of several SGAs in the last decade, no new major antipsychotic products were launched in the US during the five years leading up to our 2007 sample period . Over the last fifteen years, controversy regarding relative efficacy and tolerability of the six atypicals has persisted, but prescribers have learned about these drugs by observing how their patients responded, reading the clinical literature, and interacting with other professionals. These experiences have enabled prescribers to select a location along the diversification-concentration prescribing continuum. By 2007, five years after the launch of the last SGA, how concentrated or diversified was their prescribing behavior? We have two striking initial findings.

First, concentration appears to be the dominant behavior. Among prescribers who wrote at least one atypical antipsychotic prescription in 2007, the average share of atypical prescriptions written for the prescriber's favorite antipsychotic was 66%. Second, rather than exhibiting "herding" behavior, prescribers are quite diverse in their concentration behavior, choosing different favorite drugs, i.e., doing it "my way". To mitigate the possible impacts of very low volume prescribers, we limit the sample to all prescribers who in 2007 wrote at least 12 prescriptions for an antipsychotic (at least one a month), at least one of which was an atypical. When we further limit the sample to very highly concentrated prescribers – those for whom in 2007 at least 75% of the atypical prescriptions written were for one drug (n=6,175), we find 55% (3,379) chose Seroquel as their favorite drug, 28% (1,733) concentrated on Risperdal, 13% (775) focused on Zyprexa, 3% (173) on Abilify, 2% (93) on Geodon, and 0.4% (22) on

clozapine.[13] Incidentally, 2007 national market shares of the six atypicals were Seroquel 36.2%, Risperdal 27.2%, Abilify 13.8%, Zyprexa 13.1%, Geodon 7.3%, and clozapine 2.4%.

We conclude from this initial data examination that relatively concentrated prescribing behavior is the norm for atypical antipsychotics (a preference for one therapy for almost all patients), but that there is substantial diversity among prescribers concerning what is their favorite drug. These initial diverse prescriber concentration behavior findings raise an intriguing issue: The highly publicized regional variation literature documents that within region treatments of selected conditions for Medicare patients are relatively homogeneous compared to very large between region differences in treatments and costs.[14] Is there a corresponding between-region variability in antipsychotic prescribing behavior, or is most variability physician-specific and are regions relatively homogeneous? How does prescribing concentration vary with geographical aggregation? To address this issue, we need to define alternative regional geographical aggregates, and develop a measure of concentration behavior.

Although county, state and national aggregates are obvious, within the Dartmouth Atlas Project hospital referral regions (HRRs) have played a prominent role. HRRs represent regional health care markets for tertiary medical care that generally require the services of a major referral center, primarily for major cardiovascular surgery procedures and neurosurgery; HRRs have been developed by and are maintained by the Dartmouth Atlas Project.[15] HRRs may cross state and county borders because they are determined solely by migration patterns of patients. To relate our initial findings to the regional variation literature, we will examine mean antipsychotic prescriber concentration (and its variability) alternatively at the individual prescriber, county, HRR, state and national levels.

There are various ways one can measure the concentration behavior of prescriber i, C_i. Within the economics literature, a well-known measure of industry concentration is the Herfindahl-Hirschman Index (HHI). For a given industry or market, first rank the j = 1,…J firms by some measure of size (e.g., revenues, employment, profits) with the first being the largest firm and the last the smallest. Then for

each firm compute its industry share s_j as its size measure divided by the total industry size measure, where the s_j share is between 0 and 100. Then square the shares and sum up over the j firms, yielding HHI = $\sum_j s_j^2$. Note that the HHI ranges from zero to 10,000, with higher HHIs indicating greater concentration.[16] In the current context of individual physician prescribing behavior, we will use the number of prescriptions written for a particular drug molecule divided by the total number of antipsychotic prescriptions written by the prescriber in 2007 to compute shares and then construct HHIs. Therefore a high HHI means that the individual prescriber is using one or at most several drugs predominately, while a low HHI implies s/he prescribes in a more varied manner.[17] Using the same sample of 19,537 prescribers who prescribed at least 12 antipsychotics in 2007, we compute mean HHIs and their variability (both standard deviations and coefficients of variation) at alternative levels of regional aggregation. Results are given in Table 1.

Table 1: Means, Standard Deviations and Coefficients of Variation for Antipsychotic HHIs Alternative Geographical Aggregates, 2007

Geographical Aggregate	Mean HHI	Std. Dev.	Coef. Var.	N
Individual Prescriber	4946	2499	0.505	19537
County	3234	1773	0.548	1904
Hospital Referral Region	1989	359	0.180	306
State (plus District of Columbia)	1859	16	0.027	51
Nation	1825	na	na	1

IMS Health Incorporated Xponent™ 2007 data general prescriber sample data. HHI is calculated using 2007 antipsychotic market shares.

At the individual prescriber level, prescribing behavior is very concentrated (HHI is almost 5000), but there is also substantial variability, with the coefficient of variation being just over 0.5. However, as one aggregates into larger regions, not only is less concentrated prescribing observed, but so too is less relative variability, particularly as one moves from the county to the HRR geographical aggregate. In particular, 95% of the difference in mean HHI between individual prescriber and national level shares

disappears at the HRR level, and 99% disappears at the state level. In his survey of regional variability of various surgical procedures, Phelps [1992, pp. 25-26] categorizes coefficients of variation in the 0.1 to 0.2 range as revealing "low variability", while those at 0.4 and greater are termed "high variability" procedures. Within that classification scheme, antipsychotic prescribing behavior is highly variable at the individual prescriber and county level, but is low variability behavior at the HRR and larger regional aggregates. We conclude that while prescribing behavior is relatively concentrated at the level of the individual prescriber, and is considerably less concentrated at the county level, at both the individual prescriber and county level, antipsychotic prescribing behavior is highly variable. At the HRR level of aggregation, however, there is relatively little between-region variability, and prescription drug shares closely mimic national trends.

This preliminary evidence leads us to focus on individual prescriber rather than HRR variability, and to inquire what theory of individual prescriber learning and treatment behavior can help us understand this non-uniform concentration behavior. Is the theory also able to generate some predictions that can be assessed empirically? To those issues we now turn our attention.

IV. TOWARDS A THEORY OF PRESCRIBER LEARNING AND TREATMENT BEHAVIOR

A. ALTERNATIVE EXPLANATIONS FOR DIFFERENTIALLY CONCENTRATED PRESCRIBING

We observe that when physicians see similar patients with schizophrenia the treatments they prescribe for these patients vary relatively little within a given prescriber practice, but vary greatly across individual prescriber practices. This is consistent with the "ready-to-wear" vs. "custom-made" primary care physician behavior observed by Frank and Zeckhauser [2007], but is particularly striking here because schizophrenia and related illnesses require chronic maintenance rather than acute, episodic treatment. The economics and strategy literature offers many explanations for different actors persistently responding in diverse manners when faced with the same situations. These explanations

generally fall into one of the following four groups: perception, motivation, administration, and inspiration, which we now briefly summarize.[18]

Perception:

Physicians may disagree about the best treatment for a particular patient. For example, suppose two medical studies arrived at different conclusions. One physician reads only one study, while the other physician only reads the other. In this case, both physicians are choosing what they believe is the best treatment for their patients and yet still choose to treat them in different ways. Physicians may persist in choosing different treatment regimes as long as they do not observe the outcomes of the other physician's patients, or gain access to the article read only by the other physician.

Motivation:

If physicians instead agreed on the most appropriate treatment but do not have the motivation to prescribe the optimal treatments for their patients, one may also observe very different prescribing decisions for each physician. If there is weak competition among physicians for patients, if knowledge concerning which physicians are obtaining the most successful outcomes for their patients is difficult to obtain, and/or if physicians' prescribing behavior is reinforced by contacts with pharmaceutical sales representatives vying for the allegiance of each prescriber, then to the extent physician-sales representative alliances were heterogeneous, we would expect to observe strong brand allegiances among physicians, and that these allegiances would be to different medicines.[19]

Administration:

Alternatively, it could be that physicians have reached a consensus regarding what is the best treatment regime for a patient, and they may also want to give their patients the best care possible, but physicians face administrative or financial constraints preventing them from giving their patients the best treatment. For example, if the best treatment is drug A but only drug B is covered by a particular health plan's formulary, one may observe physicians using drug A whenever they can and drug B in all

other cases. In this context one would observe very different prescribing behavior across physicians because their patients have different insurance coverage. In the context of antipsychotic drugs, however, Medicaid (the dominant payer for patients with schizophrenia), placed little if any restrictions on choice among the atypicals during our 2007 sample period; Medicare Part D required that any private prescription drug plan offer all but one of the atypical antipsychotic drugs on its formulary, and many other private insurers had similar formulary provisions.[20]

Inspiration:

Yet another alternative is that physicians may have prior beliefs about what is the best treatment for their patient, but they may either need to learn more about the drug to use it effectively or there may be considerable uncertainty regarding whether they have correct beliefs concerning the efficacy and tolerability of each drug. In either context, as physicians treat more patients they learn from patients' responses to each drug.

Although we do not *a priori* rule out the first three explanations underlying differentially concentrated prescribing behavior, in the following section we outline a model that formalizes one version of the inspiration intuition and offers a basic framework leading to our subsequent more detailed empirical analyses. It also builds on the Frank and Zeckhauser [2007] "sensible-use-of-norms" hypothesis.

B. A MODEL OF PRESCRIBER LEARNING WITH INCOMPLETE INFORMATION

Assume patients arrive sequentially to be seen by a physician and are indexed by $p \in \mathbf{N} = \{1, 2, \ldots\}$. A new patient arrives at a physician's office at the beginning of each time interval w, i.e. patient p arrives at the physician's office at the point in time pw, w later than patient $p-1$ who arrived at $(p-1)w$. Let the continuous time discount rate be given by r. A patient p has the combination of symptoms observable by the physician and denoted by s where s is randomly drawn from the set of all possible symptoms, $\mathbf{S} = \{1 \ldots S\}$. The set of available drugs that treat these symptoms consists of $\mathbf{D} = \{1 \ldots D\}$. The

maximum possible benefit of drug d for symptom *s* is B_{sd}. The best drug treatment for a given set of symptoms is indicated by $d^*(s)$, i.e. $B_{sd^*(s)} > B_{sd}$ for all $d \neq d^*(s)$. Assume the physician knows B_{sd} for all combinations of *s* in ***S*** and *d* in ***D***.

The therapy for a patient is comprised not only of the drug, *d*, that the physician prescribes, but also any complementary actions, *a*, that the physician undertakes, such as adjusting the dosage of the drug (a process known as titrating), or any actions that affect the patient's adherence and outcomes, such as communicating information on expected possible side effects and their duration. In order to achieve the maximum potential benefit from a drug, the physician must simultaneously undertake the ideal complementary actions. In particular, the realized effectiveness of drug *d* prescribed for patient *p* with symptoms *s* is

$$b_{sdp} = B_{sd}[1 - (a - x_{dp})^2] , \quad (1)$$

where *a* denotes complementary actions the physician undertakes, and

$$x_{dp} = \vartheta_d + \varepsilon_{dp} . \quad (2)$$

We assume ϑ_d and ε_{dp} are independent normally distributed random variables for all *d* and *p*, with mean zero and variances σ^2_d and σ^2_ε, respectively.

This formulation implies that the maximum benefit of a drug is achieved when $a = x_{dp}$. As $|a - x_{dp}|$ increases, the realized benefit from drug *d,* b_{sdp}, decreases. Given the squared difference, the decrease in realized benefit occurs at an increasing rate with the size of the gap.

After prescribing drug *d* to patient *p* and undertaking complementary actions *a*, the physician observes x_{dp}. That is, the physician observes the complementary action that would have been optimal for the patient just treated, given the drug that was prescribed for that patient. Note that the physician does not observe $x_{d'p}$ for $d' \neq d$ (i.e., the ideal actions had that patient been given another drug) or $x_{dp'}$ for $p' \neq p$ (i.e., the ideal actions for another patient given that drug).

Recall the physician knows the maximum potential benefit from each drug B_{sd} as well as the distribution from which ϑ_d and ε_{dp} are drawn. Therefore the only uncertainty the physician faces is what complementary actions will work best for a particular drug and a particular patient. Jovanovic and Nyarko (1996) have a similar feature in their model. This model differs from the multi-armed bandit model in which the effectiveness of each drug B_{sd} would be unknown and there would be no complementary actions.

It is useful to discuss the intuition underlying this model. Here the physician learns by taking different complementary actions *a* when prescribing drug *d* and observing afterwards the impact on that patient, x_{dp}. The fact that the physician does not observe ϑ_d implies that s/he typically cannot learn everything s/he needs to know about a drug from treating a single patient. Note that for simplicity we assume that the best action that the physician can potentially learn to make, ϑ_d, depends only on the drug prescribed but not on the symptoms. Symptoms in turn determine which drug has the highest potential for giving a patient the best outcomes, d*(s). We have also assumed that the speed of learning the complementary action ϑ_d for each drug *d* depends on only how often the physician prescribes drug *d*, not on the patients presenting with symptoms for whom s/he prescribes this drug.

Denote the physician's prescription and outcome history through patient *p* by $h_p = (h_{1,p}, h_{2,p}, \ldots, h_{d,p}, \ldots, h_{D,p})$ where $h_{d,p}$ is determined recursively by:

$$\begin{aligned} h_{d,p} &= \text{empty if } p=0; \\ &= h_{d,p-1} \text{ if } d_p(s_p, h_{p-1}) \neq d \text{ and } p>0; \text{ and} \\ &= (h_{d,p-1}, x_{dp}) \text{ if } d_p(s_p, h_{p-1}) = d \text{ and } p>0. \end{aligned} \qquad (3)$$

The physician's policy is to choose a drug, $d_p(s, h_{p-1})$, and complementary actions, $a_p(d, h_{p-1})$, for each patient p with symptom s and each history h_{p-1}. Since complementary actions *a* do not affect learning about ϑ_d, the optimal complementary actions *a* and physician's expected per patient payoff from patient *p* are given by:

$a_p(h_{p-1}) = E[\vartheta_d | h_{d,p-1}]$, and

$E[b_{sdp} | h_{d,p-1}] = B_{sd}(1 - Var(\vartheta_d | h_{d,p-1}) - \sigma_\varepsilon^2)$. (4)

From these equations we see that the more times a physician has used drug *d*, the closer s/he will expect to be to achieving the second-best benefits of the drug *d* on a patient with symptoms *s*, $B_{sd}(1- \sigma_\varepsilon^2)$.

If the physician is myopic (i.e., s/he only cares about the current patient's outcome and not about any future patients' outcomes), then the optimal prescribing decision is simply

$$d_{p,}(s_{p,}, h_{p-1}) = \arg\max_{d} E[b_{sdp} | h_{p-1}]. \quad (5)$$

If the physician is not myopic (i.e., s/he cares about maximizing the expected discounted patient benefit of all patients s/he expects to see over time), then the physician's optimization problem is

$$\max_{d_p()} E(\sum_{p=1}^{\infty} e^{-rwp} E[b_{sdp} | h_{p-1}]). \quad (6)$$

We now consider the empirical predictions emanating from this learning model.

C. PREDICTIONS OF THE MODEL

Suppose first that w is large (i.e., the physician is a low-volume prescriber). In this case, over time the physician will concentrate on a subset of drugs. Moreover, this subset of drugs will depend on the initial history of idiosyncratic patients' symptoms presented to the physician. Both the number of drugs and the identity of the drugs for which the physician concentrates depend on the initial history of symptom presentation to the physician. The intuition behind this is as follows. If the physician observes a sequence of patients with a given symptom set *s*, then s/he chooses an appropriate drug, say *d*, for them. The physician will learn a great deal about this drug *d* and will be unwilling to switch to another drug *d'* when s/he sees a patient with specific symptom set *s'* (even if *d'* would be more appropriate for *s'* if the physician had the same knowledge about drugs *d* and *d'*).

More formally, consider a physician's choice for a patient with symptoms *s'* between two drugs *d'* and *d*. If the physician is myopic then his/her expected utility from using drugs *d'* and *d* is given by

$$B_{s'd'} (1 - Var(\vartheta_{d'} | h_{d',p-1}) - \sigma_\varepsilon^2), \quad (7)$$

$$B_{s'd} (1 - Var(\vartheta_{d} | h_{d,p-1}) - \sigma_\varepsilon^2). \quad (8)$$

Therefore, the myopic physician is trading off the difference between $B_{s'd'}$ and $B_{s'd}$ against the difference between $Var(\vartheta_{d'} | h_{d',p-1})$ and $Var(\vartheta_{d} | h_{d,p-1})$. If the maximum potential benefit from drug *d'*, $B_{s'd'}$, is greater than that of drug *d*, $B_{s'd}$, but the physician prescribed drug *d* more often than drug *d'* in the past so that $Var(\vartheta_{d} | h_{d,p-1}) < Var(\vartheta_{d'} | h_{d',p-1})$, then s/he may prefer to choose drug *d*. Note also that because the complementary actions of a physician are not observed by other physicians, there is no spillover learning. In particular, learning the market shares of the drugs that other physicians are prescribing is no help in learning a drug's ideal complementary actions.

As w is decreased (i.e., the volume of patients seen by the physician increases), the model implies that physicians have a larger incentive to invest in learning how to use new or different drugs effectively. Therefore we would expect to see more diverse prescribing with increases in patient volume, *ceteris paribus*. The set of drugs a physician uses will still depend on the initial history of symptoms of the patients the physician has seen, but this dependence will be weaker.

Finally, as w decreases to zero (i.e., the physician sees patients almost continuously), the set of drugs that physicians will prescribe may be equal to the universe of drugs, *D.* More formally, if we assume that there are sufficiently many different symptoms such that each drug *d* in ***D*** is optimal for some symptoms *s* in ***S***, $d^*(s)=d$, then a very high-volume physician will eventually learn a great deal about optimal complementary actions ϑ_d for each drug *d* in ***D*** and prescribe $d^*(s)$ for every *s*.

Anticipating our empirical context, we note that physician specialties that are likely to see particularly large numbers of patients with symptom set *s* can be expected to have greater incentives to invest in learning about different drugs than those specialties rarely encountering such patients. To the

extent the symptom set *s* presented to the physician is heterogeneous, given patient volume, so too will be the range of drugs prescribed.

This framework implies that we would expect low-volume physicians to concentrate more than high-volume physicians. In addition we would expect the treatment regimes among low-volume physicians to vary a great deal more than among high-volume physicians, since the treatment decisions of low-volume physicians depend much more on their idiosyncratic random patient history than do those of high-volume physicians.

Similarly to differences in patient arrival rate, *w*, physicians with higher discount rates, *r*, would be less likely to experiment with more drugs. Therefore, all else equal, we would expect physicians with higher discount rates to have more concentrated prescribing. If one believes older physicians approaching retirement discount the distant future more heavily than younger physicians, then conditional on histories of their patients, we would expect older physicians nearing retirement to experiment less and to concentrate more.

To illustrate these comparative-static results (and the logic of the model more generally), consider the following simple example. There are two drugs d_1 and d_2, and two symptoms s_1 and s_2. Before seeing any patients, the physician has the same uncertainty about the ideal complementary action for each drug, ϑ_d; that is, $\sigma_d^2 = \sigma^2$. Suppose, however, that the physician learns the ideal complementary action precisely after a single prescription; that is, $\sigma_\varepsilon^2=0$. To make the analysis interesting we assume that $d_i^*(s_i)=s_i$ for $i \in \{1, 2\}$ which is equivalent to $B_{11}>B_{12}$ and $B_{22}>B_{21}$. Note that we do not assume that the benefits are symmetric, because asymmetries generate additional interesting insights. Finally, we assume that symptoms s_1 and s_2 are equally likely.

First, suppose that the physician is myopic. Clearly, in the first period the physician prescribes the best drug. There are three cases concerning what happens next:

1. The physician always prescribes the drug that she prescribed in the first period. This case is realized iff $B_{12} > B_{11}(1-\sigma^2)$ and $B_{21} > B_{22}(1-\sigma^2)$.
2. If the physician prescribed d_1 in the first period, then she prescribes d_1 thereafter. If the physician prescribed d_2 in the first period, then she prescribes the best drug $d_i^*(s_i)$ thereafter. This case is realized iff $B_{12} > B_{11}(1-\sigma^2)$ and $B_{21} < B_{22}(1-\sigma^2)$.
3. The physician always prescribes the best drug $d_i^*(s_i)$. This case is realized iff $B_{12} < B_{11}(1-\sigma^2)$ and $B_{21} < B_{22}(1-\sigma^2)$.

Second, suppose that the physician is not myopic. To make the analysis interesting, we assume that Case 1 is realized if the physician is myopic: $B_{12} > B_{11}(1-\sigma^2)$ and $B_{21} > B_{22}(1-\sigma^2)$. Finally, for definiteness we assume that the physician is more tempted to concentrate on d_1 rather than d_2, in the sense that

$$\frac{B_{12} - B_{11}\left(1-\sigma^2\right)}{B_{11} - B_{12}} > \frac{B_{21} - B_{22}\left(1-\sigma^2\right)}{B_{22} - B_{21}}.$$

This last assumption guarantees that the two critical values of δ satisfy $\delta_L < \delta_H$ below. Depending on the discount factor $\delta = e^{-rw}$, we again have three cases:

1. The physician always prescribes the drug that she prescribed in the first period. This case is realized if the physician is sufficiently impatient (or, equivalently, low-volume) that $\delta < \delta_L$.
2. If the physician prescribed d_1 in the first period, then she prescribes d_1 thereafter. If the physician prescribed d_2 in the first period, then she prescribes the best drug $d_i^*(s_i)$ thereafter. This case is realized if the physician is moderately patient (or, equivalently, moderate-volume) such that $\delta_L < \delta < \delta_H$.
3. The physician always prescribes the best drug $d_i^*(s_i)$. This case is realized if the physician is sufficiently patient (or, equivalently, high-volume) that $\delta > \delta_H$.

The critical values δ_L and δ_H are given by:

$$\frac{\delta_H/2}{1-\delta_H/2} = \frac{B_{12} - B_{11}\left(1-\sigma^2\right)}{B_{11} - B_{12}},$$
$$\frac{\delta_L/2}{1-\delta_L/2} = \frac{B_{21} - B_{22}\left(1-\sigma^2\right)}{B_{22} - B_{21}}.$$

D. LIMITATIONS OF THE MODEL

Although this model has several clear predictions, it is limited in a number of ways. First, in this model physicians fully know the basic "quality" B_{sd} of each drug, i.e., its maximum potential benefit; they only do not know what complementary actions should be taken with each particular drug. In particular this implies that physician knowledge of the national or local market share of each drug should not affect the physician's decisions. This is in contrast to simple models of "herding" behavior, for in our framework differences in behavior persist even when prescribers observe nation-wide market shares.[21]

Second, and related, the physician learns only from her/his own experience. A richer model would incorporate learning over time from colleagues and market/scientific reports about drugs and optimum complementary actions.

Third, in this model even if a physician's payoffs are minimally related to patients' payoffs, since the physician's objective is proportional to the patients' payoffs (even if the proportional constant is small), the physicians' prescribing decisions are socially optimal. For example, if the physician's payoff is 1% of a patient's utility, then the physician's prescription decisions are as if s/he incorporated the full value of the decision. In other words, the problem does not change if one rescales B_{sd}. This observation implies that the only role the social planner can play in this model if s/he has the same discounting as the physician is to provide the physician with information from other physicians. A more realistic model would include costs and benefits of learning about a drug from other sources.

We now describe the data utilized in our analysis, and then we will evaluate the extent to which the predictions of this model are consistent with prescribing behavior observed in our data.

V. PRESCRIBING BEHAVIOR DATA

Our prescriber behavior data are taken from the IMS Xponent data source that tracks prescribing behavior by linking individual retail and mail order dispensed pharmacy prescriptions to the prescriber identification number. A 10% random sample of all prescribers who wrote at least one antipsychotic prescription in 1996 was drawn, and these prescribers are followed on a monthly basis from January 1996 through September 2008. Each year after 1996 the sample is refreshed by adding a 10% sample of new antipsychotic prescribers. These prescribers are "new" in the sense that they are new to the sample; they may have been prescribing antipsychotics for many years.

We aggregate various specialties into five groups. Primary care physicians ("PCPs") include internal medicine, family medicine and practice, pediatrics, and general practice prescribers. Another group of prescribers is psychiatrists ("PSY"), which not only includes general psychiatry but also child - adolescent and geriatric psychiatry. The neurologist group ("NEU") includes those in general neurology, as well as geriatric and child neurologists. A fourth group of prescribers encompasses non-physicians ("NPs"), primarily nurse practitioners and physician assistants.[22] Many states have licensed nurse practitioners and certain physician assistants to write prescriptions, under varying physician supervision provisions. In one survey of nurse practitioners, almost one-third of patients they treated were seen for mental health problems.[23] We designate all other prescribers as other ("OTH").

As seen in Table 2, although PCPs comprise about 50% of our sample of 19,737 prescribers, in 2007 they and the relatively populous OTH group of prescribers wrote relatively few antipsychotic and atypical prescriptions, averaging less than six per month. In contrast, PSYs averaged more than 600 antipsychotic (550 atyical) prescriptions annually, several times the second leading prescribers – NPs, with about 175 antipsychotic (155 atypical) prescriptions annually. NEU prescribers write on average almost 100 antipsychotic prescriptions annually, about 80 of which are for atypicals.

Table 2: Mean Values of Characteristics of 2007 Prescriber Sample, by Prescriber Specialty

Specialty	Number	Antipsychotic Annual Rx's	Atypical Annual Rx's	No. Distinct Antipsychotics	No. Distinct Atypicals	Antipsy-chotic HHI	Atypical HHI
NEU	728	97.64	82.30	3.60	2.33	5,657	7,025
PCP	9,544	68.03	52.82	4.31	2.73	4,612	5,915
PSY	3,463	609.56	551.37	7.46	4.71	3,245	3,661
NP	1,641	174.85	155.30	4.29	2.88	5,181	5,633
OTH	4,161	54.24	29.53	2.76	1.65	6,912	7,081

Notes: NEU – general, geriatric and child neurologists; PCP – primary care physicians, internal medicine, family medicine and practice, pediatrics, and general practice; PSY – general, child-adolescent and geriatric psychiatry; NP – non-physician prescribers, nurse practitioners and physician assistants; OTH – all other prescribers.

All values calculated using IMS Health Incorporated Xponent™ general prescriber sample 2007 data for prescribers writing at least 12 antipsychotic prescriptions.

In terms of concentration of prescribing behavior, while PSYs are the highest volume prescribers, they treat with on average the largest distinct number of antipsychotics (7.46) and atypicals (4.71), and exhibit the least concentrated antipsychotic (atypical) prescribing behavior, having on average an HHI of 3,245 (3,661); in contrast, OTH physicians are the lowest annual volume prescribers, use the smallest number of distinct antipsychotic (2.76) and atypical (1.65) molecules, and are the most concentrated antipsychotic and atypical prescribers, having HHIs of 6,912 and 7,081, respectively. While NPs are the second only to PSYs in terms of annual prescriber volume, in terms of both the variety of drugs they use and their concentration, their behavior is quite similar to that of the relatively low volume PCPs.

We link the prescriber identifiers in the IMS Xponent data base to the American Medical Association ("AMA") directory of physicians. Notably, while the AMA Masterfile Directory has education, training, specialty certification and demographic data on most physicians and type of practice

as of 2008, there is no comparable data available on NP nurse practitioners or physician assistants and therefore for our subsequent empirical analyses we exclude all NPs.[24]

Several features of the physician data set are worth noting. First, we have data on only physicians/NPs and their prescribing behavior, not on the patients they see. Second, IMS keeps track of prescribers that are deceased or retire, using look-back windows with no prescribing activity for one year forward and one year backward. Third, because 1996 antipsychotic prescribers are followed through September 2008 (unless they die or retire), as the sample time frame becomes more recent, the set of prescribers in the sample is likely older than would be observed in an entirely new random sample drawn in, say, 2007.[25]

VI. *EMPIRICAL FRAMEWORK*

While the conventional HHI described earlier measures concentration, it cannot distinguish well between different patterns of concentration. In a duopoly, for example, with firms A and B, one obtains the same HHI if firm A has 80% market share and firm B has 20% as with the reverse situation in which A has 20% market share and B has 80%. Our theoretical framework suggests we focus not only on concentration, but also on the diversity of concentration. This suggests an alternative measure of concentration that focuses on the deviation of concentration from national trends. Consider physician i prescribing drug j in geographical region r, and denote the share of prescriptions written by this physician for drug j as s_{ijr}. Let the overall market share of drug j in region r be m_{jr}, where both s_{ijr} and m_{jr} are between zero and 100. As a measure of the deviance of physician i's prescribing behavior from that of the aggregate regional physicians' market share, we calculate

$$D_{ijr} = \sum_j (s_{ijr} - m_{jr})^2 . \qquad (9)$$

If every physician in region r had the same prescribing share, D_{ijr} would equal zero. As physician prescribing behavior heterogeneity (homogeneity) within region r increases, D_{ijr} increases (decreases).[26]

The regression specification we will take to the data is of the following general form:

$$C_i = \alpha Age_i + \beta Volune_i + \varphi X_i + \varepsilon_i \quad (10)$$

where X is a vector of covariates described below. As several of our measures of concentration will by construction take on values only within a given interval (for example HHI will be between 0 and 10,000, and is censored above 10,000), we take account of this in our analysis by employing appropriate econometric estimation methods. In some regressions we specify interaction variables, particularly among measures of volume and physician specialty.

Regarding covariates, the age of the prescribing physician is taken from the AMA Masterfile Directory. In our empirical analysis we use age quartiles as indicator variable regressors instead of merely the raw age of the physician. This allows us to evaluate whether young physicians or those near retirement use technology in similar or different ways, perhaps nonlinear in age.

While we do not have any information about patients, several physician practice setting variables will help us partially to control for the patient mix seen by a given physician. In particular, we observe the specialty of the physician as well as whether the physician is hospital or office based, and the county/region in which the practice is located.[27] We expect, as Table 2 reports, that specialty is also correlated with antipsychotic prescribing volume.

In terms of differential learning costs, we might expect the learning costs for physicians to vary depending on their training and/or current practice environment. In particular in our analysis we will control for whether the physician practices in a group or has a solo practice, the size of the county in which the physician practices, and whether of the physician has an MD or DO degree.[28]

Finally we might expect women and men to use technology in somewhat different ways. Therefore, in our analysis we control for the gender of the physician. In addition some physicians ask that their prescribing data not be shared with pharmaceutical or other for-profit organizations. We will

examine whether these physicians appear to differ from other physicians in their concentration and deviation prescribing behavior.

In Table 3 below we provide summary statistical information for both the dependent and explanatory variables we use in our analysis.

Table 3: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
Deviation of Physician's Antipsychotic prescribing from HRR Shares	17,652	2,660	2,441	5	**10,321**
Deviation of Physician's Antipsychotic prescribing from National Market Shares	17,652	2,735	2,499	30	**10,051**
HHI of Individual Physician's Antipsychotic Prescribing	17,652	4,920	2,484	1,196	**10,000**
HHI of Individual Physician's Atypical Prescribing	16,262	5,708	2,498	1,701	**10,000**
% of Prescriptions for Antipsychotics that were for Atypicals	17,652	71.46	32.60	0	**100**
Number of Different Antipsychotics Prescribed	17,652	4.54	2.70	1	**17**
Number of Different Atypicals Prescribed	17,652	2.85	1.64	0	**6**
Total Yearly Antipsychotic Prescriptions	17,652	171.80	431.35	12	**7,186**
Total Yearly Atypical Antipsychotic Prescriptions	17,652	145.92	388.51	0	**6,780**
Prescriber Age	17,652	50.37	10.80	26	**92**
PCP	17,652	0.54	0.50	0	**1**
PSY	17,652	0.19	0.40	0	**1**
NEU	17,652	0.04	0.20	0	**1**
OTH	17,652	0.23	0.42	0	**1**
Solo Practice	17,652	0.20	0.40	0	**1**
Population (county)	17,652	1,065,738	1,810,008	1,299	**9,734,701**
Female	17,652	0.26	0.44	0	**1**
Hospital Based Physician	17,652	0.08	0.27	0	**1**
DO Flag	17,652	0.09	0.28	0	**1**
Physician Opt Out	17,652	0.03	0.18	0	**1**

All values calculated using IMS Health Incorporated Xponent™ general prescriber sample 2007 data.

The reference group in all our regressions is a young (under age 43) physician, practicing in a county with less than 150,000 residents, who has an MD degree, is not hospital based, did not request that his/her prescribing information be withheld for companies interested in it for marketing purposes, and whose specialty is one that typically does not prescribe many antipsychotics (OTH). All coefficient

estimates therefore compare how the prescribing behavior of a particular physician having different characteristics compares to physicians in the excluded reference group.

VII. *RESULTS*

We begin our empirical analysis by examining which physicians use a wider variety of drug molecules. We employ two measures of variety. The first measure is the number of distinct antipsychotic drug molecules prescribed in 2007, while the second is the HHI of their prescriptions in 2007. We examine these both across all antipsychotic prescribing as well as just atypical prescribing.

A. Use of Diverse Technology: Number of Distinct Drug Molecules Prescribed[29]

We first estimate a Poisson specification relating the number of distinct antipsychotic drugs a physician prescribes in 2007 to a host of explanatory variables and then using a similar specification we estimate the number of different atypical drugs a physician prescribes during that year; the former involves a maximum of 17 antipsychotics, and the latter six atypicals. As seen in Tables 4 and 5, the estimates reveal that, holding other factors fixed, PSYs prescribe the largest number of distinct drugs (for all antipsychotics, and only atypicals), followed by PCPs, NEUs, and OTH (the excluded group). In addition, estimates on the physician-specialty volume interaction variables indicate that while for all specialties higher volume physicians employ a larger number of distinct molecules (both atypicals and antipsychotics), volume matters most for physician specialists who are relatively low-volume prescribers, OTHs and PCPs. Across specialties, training and patient volume/experience appear to be substitutes. In addition as they age, older physicians use more antipsychotics overall, however this trend abates as physicians approach retirement age; we observe the oldest quartile of physicians using only slightly more distinct antipsychotics than the youngest quartile (borderline statistical significance). When examining physicians' use of atypicals, however, we observe the only significant age coefficient is that on the oldest quartile (59+), who prescribe fewer distinct atypicals. For physicians approaching retirement, the difference in prescriber-age effects for the overall antipsychotic versus atypical only

suggests that the oldest physicians are disproportionate users of distinct older conventional antipsychotics.

Table 4: Poisson Regression on Number of Distinct Antipsychotic Drug Molecules Prescribed in 2007

	Coefficient	Standard Error	P>|z|
Total Yearly Antipsychotic Prescriptions	0.001039	0.000048	<.001
PCP*Total Yearly Antipsychotic Prescriptions	-0.000366	0.000051	<.001
PSY*Total Yearly Antipsychotic Prescriptions	-0.000792	0.000049	<.001
NEU*Total Yearly Antipsychotic Prescriptions	-0.000472	0.000071	<.001
Age Quartile 43-50*	0.0374	0.0102	<.001
Age Quartile 51-58*	0.0513	0.0101	<.001
Age Quartile 59+*	0.0186	0.0107	0.081
PCP*	0.4520	0.0115	<.001
PSY*	0.8965	0.0129	<.001
NEU*	0.2608	0.0233	<.001
Female*	-0.0899	0.0084	<.001
Population 150,000-500,000 (county)*	-0.0357	0.0099	<.001
Population 500,000-1,000,000 (county)*	-0.0742	0.0105	<.001
Population more than 1,000,000 (county)*	-0.0692	0.0101	<.001
Solo Practice*	-0.0019	0.0091	0.831
Hospital Based Physician*	0.0085	0.0125	0.497
DO Flag*	0.0334	0.0129	0.010
Physician Opt Out*	0.0120	0.0190	0.530
Constant	0.9876	0.0141	<.001
Number of Observations= 17,652			
Pseudo R^2= 0.145			

*Indicates dummy variable. All values calculated using IMS Health Incorporated Xponent™ general prescriber sample 2007 data, and population estimates from the US Census Bureau.

Physicians in larger counties use somewhat fewer distinct antipsychotic and atypical molecules, however the size of the county seems to matter less when comparing counties with more than 500,000 residents. For all antipsychotics and for only atypicals, female prescribers use less variety relative to male prescribers, but this effect is significant only for all antipsychotics. Prescribing variety is unrelated to office practice type, whether hospital affiliated, and whether the physician restricts use of prescribing

data. Finally we observe that physicians with a DO instead of a MD degree use a wider variety of drug molecules.

Table 5: Poisson Regression on Number of Distinct Atypical Molecules Prescribed in 2007

	Coefficient	**Standard Error**	**P>|z|**
Total Yearly Antipsychotic Prescriptions	0.001059	0.000061	<.001
PCP*Total Yearly Antipsychotic Prescriptions	-0.000405	0.000066	<.001
PSY*Total Yearly Antipsychotic Prescriptions	-0.000937	0.000062	<.001
NEU*Total Yearly Antipsychotic Prescriptions	-0.000478	0.000089	<.001
Age Quartile 43-50*	0.0113	0.0127	0.375
Age Quartile 51-58*	0.0152	0.0126	0.230
Age Quartile 59+*	-0.0423	0.0134	0.002
PCP*	0.5093	0.0148	<.001
PSY*	1.0558	0.0166	<.001
NEU*	0.3502	0.0292	<.001
Female*	-0.0308	0.0105	0.003
Population 150,000-500,000 (county)*	-0.0460	0.0126	<.001
Population 500,000-1,000,000 (county)*	-0.0900	0.0132	<.001
Population more than 1,000,000 (county)*	-0.0868	0.0127	<.001
Solo Practice*	-0.0086	0.0115	0.452
Hospital Based Physician*	-0.0124	0.0160	0.437
DO Flag*	0.0518	0.0161	0.001
Physician Opt Out*	0.0348	0.0238	0.144
Constant	0.4958	0.0179	<.001
Number of Observations= 17,652			
Pseudo R^2= 0.1045			

*Indicates dummy variable. All values calculated using IMS Health Incorporated Xponent™ general prescriber sample 2007 data, and population estimates from the US Census Bureau.

B. New vs. Old Drugs

Instead of focusing on absolute numbers of distinct drugs prescribed, we next examine the share of a physician's antipsychotic prescriptions that are written for atypicals. Since the percent of atypicals can at most be 100, we employ a Tobit regression to estimate how various characteristics of

the physician affect the share of antipsychotic prescriptions written for atypicals. Results of this Tobit regression are presented in Table 6.

Table 6: Tobit Regression (Marginal Effects Estimated at Variable Means) on Percent of All Antipsychotic Prescriptions written for Atypicals in 2007

	dy/dx	Standard Error	P>|z|	Mean Value
Total Yearly Antipsychotic Prescriptions	0.0108	0.0061	0.074	171.80
PCP*Total Yearly Antipsychotic Prescriptions	0.0154	0.0070	0.028	36.44
PSY*Total Yearly Antipsychotic Prescriptions	-0.0155	0.0061	0.011	118.84
NEU*Total Yearly Antipsychotic Prescriptions	0.0032	0.0094	0.737	3.99
Age Quartile 43-50*	-1.77	0.760	0.020	0.252
Age Quartile 51-58*	-1.42	0.761	0.063	0.262
Age Quartile 59+*	-2.00	0.810	0.014	0.222
PCP*	17.02	0.793	<.001	0.536
PSY*	44.72	1.035	<.001	0.194
NEU*	27.66	1.660	<.001	0.041
Female*	6.68	0.640	<.001	0.263
Population 150,000-500,000 (county)*	-3.55	0.760	<.001	0.262
Population 500,000-1,000,000 (county)*	-5.65	0.796	<.001	0.225
Population more than 1,000,000 (county)*	-7.30	0.769	<.001	0.264
Solo Practice*	0.310	0.682	0.650	0.199
Hospital Based Physician*	-2.67	0.995	0.007	0.081
DO Flag*	0.103	0.970	0.915	0.086
Physician Opt Out*	2.74	1.486	0.065	0.034
Number of Observations= 17,652				
Pseudo R^2= 0.017				
Left Censored=0 Right Censored=3,353				

*dy/dx for a dumy variable represents effect of a discrete change from 0 to 1. All values calculated using IMS Health Incorporated Xponent™ general prescriber sample 2007 data, and population estimates from the US census Bureau.

As seen in Table 6, other things equal, older physicians use a lower percentage of these newer drugs than do those in the youngest quartile (under age 43), particularly the oldest quartile of physicians, although the 2.00 percentage point magnitude effect is modest. By comparison, other things equal, the atypical share is almost seven percentage points greater for female than male prescribers.

Conditional on overall volume, PSY prescribers write the largest share of atypical prescriptions, followed by NEU, PCPs, and finally OTH. However, as volume increases, high volume PCPs and high volume physicians in specialties that do not typically prescribe antipsychotics (OTH) use a larger share of atypicals, whereas high volume PSYs increasingly use older generation typical antipsychotics as their prescription volume increases. Interestingly, the share of atypical prescriptions decreases with county population size. Together these findings concerning greater use of older antipsychotics in more populous areas, particularly by high volume prescribing PSYs, could reflect greater specialization by PSYs in more urban areas, serving more heterogeneous patient populations.

In addition, we find that physicians who do not want their prescribing behavior information used for pharmaceutical marketing prescribe a larger percentage of atypicals (but this effect is only marginally significant), whereas hospital based physicians use a lower percentage of atypicals. Practice type and form of medical degree are statistically insignificant factors.

C. *Physician Prescribing HHI*

Next we examine the concentration of physician prescribing as measured by the HHI of the physician's prescriptions of all antipsychotics, and their HHI among the atypicals. Initial visual data inspection suggested a log normal distribution of HHIs, censored from above at 10,000. We therefore estimate Tobit models where the dependent variable is alternatively log of overall antipsychotic physician HHI or log of atypical physician HHI. Both regressions generate a similar pattern of findings, as is seen in Tables 7 and 8. In particular, consistent with the predictions from our theoretical model, other things equal, higher volume physicians have less concentrated prescribing behavior. We also observe that volume matters more for physicians that are either PCPs or those in OTH, again suggesting that experience and medical specialty training are substitutes; in particular, the positive coefficient estimate on the PSY-volume interaction term almost entirely offsets the negative estimate on the (implicit) OTH-volume interaction variable. Moreover, while older physicians have less concentrated

overall antipsychotic and insignificantly different atypical prescribing behavior compared to the youngest physician quartile, the one exception is that the oldest quartile of physicians exhibit more concentrated atypical prescribing, that is they utilize a smaller variety of atypicals than do all younger

Table 7: Tobit Regression (Marginal Effects Evaluated at Variable Means) on Log (Antipsychotic Prescription HHI for 2007)

	dy/dx	Standard Error	P>|z|	Mean Value
Total Yearly Antipsychotic Prescriptions	-0.000821	0.000080	<.001	171.80
PCP*Total Yearly Antipsychotic Prescriptions	-0.000149	0.000090	0.089	36.44
PSY*Total Yearly Antipsychotic Prescriptions	0.000626	0.000080	<.001	118.84
NEU*Total Yearly Antipsychotic Prescriptions	0.000359	0.000120	0.002	3.99
Age Quartile 43-50*	-0.029	0.010	0.002	0.252
Age Quartile 51-58*	-0.039	0.010	<.001	0.262
Age Quartile 59+*	-0.019	0.010	0.067	0.222
PCP*	-0.435	0.010	<.001	0.536
PSY*	-0.761	0.013	<.001	0.194
NEU*	-0.238	0.021	<.001	0.041
Female*	0.057	0.008	<.001	0.263
Population 150,000-500,000 (county)*	0.020	0.010	0.037	0.262
Population 500,000-1,000,000 (county)*	0.040	0.010	<.001	0.225
Population more than 1,000,000 (county)*	0.032	0.010	0.001	0.264
Solo Practice*	-0.005	0.009	0.582	0.199
Hospital Based Physician*	0.019	0.013	0.119	0.081
DO Flag*	-0.023	0.012	0.056	0.086
Physician Opt Out*	-0.035	0.019	0.056	0.034
Number of Observations= 17,652				
Pseudo R^2= 0.218				
Left Censored=0 Right Censored=1,571				

* dy/dx for a dummy variable represents effect of adiscrete change from 0 to 1. All values calculated using IMS Health Incorporated Xponent™ general prescriber sample 2007 data, and population estimates from the US Census Bureau.

physician quartiles. Restated in another way, the oldest physician quartile is no different from younger quartiles in its concentrated use of antipsychotic drugs, but its prescribing of new generation atypical drugs is more concentrated and less diverse. This could reflect greater familiarity with use of older first generation antipsychotics from experiences earlier in their prescribing careers.

Among specialties, holding volumes fixed, relative to OTH prescribers who have the most concentrated overall antipsychotic prescribing behavior (the omitted group), PSY are least concentrated, followed by PCPs, and NEUs; when confined to just the atypicals we observe a similar pattern.

Table 8: Tobit Regression (Marginal Effects Evaluated at Variable Means) on Log (Atypical Antipsychotic Prescription HHI for 2007)

	dy/dx	**Standard Error**	**P>|z|**	**Mean Value**
Total Yearly Antipsychotic Prescriptions	-0.001026	0.000080	<.001	182.67
PCP*Total Yearly Antipsychotic Prescriptions	-0.000051	0.000090	0.557	39.04
PSY*Total Yearly Antipsychotic Prescriptions	0.000859	0.000080	<.001	128.99
NEU*Total Yearly Antipsychotic Prescriptions	0.000384	0.000110	0.001	4.30
Age Quartile 43-50*	0.002	0.009	0.869	0.252
Age Quartile 51-58*	0.008	0.009	0.424	0.262
Age Quartile 59+*	0.055	0.010	<.001	0.223
PCP*	-0.206	0.011	<.001	0.563
PSY*	-0.708	0.013	<.001	0.210
NEU*	-0.011	0.021	0.592	0.043
Female*	0.034	0.008	<.001	0.267
Population 150,000-500,000 (county)*	0.013	0.009	0.159	0.261
Population 500,000-1,000,000 (county)*	0.052	0.010	<.001	0.225
Population more than 1,000,000 (county)*	0.047	0.010	<.001	0.262
Solo Practice*	0.017	0.009	0.046	0.201
Hospital Based Physician*	-0.003	0.013	0.805	0.079
DO Flag*	-0.029	0.012	0.014	0.088
Physician Opt Out*	-0.037	0.018	0.043	0.035
Number of Observations= 16,262				
Pseudo R^2= 0.22				
Left Censored=0 Right Censored=2,606				

*dy/dx for dummy variables represents effect of a discrete change from 0 to 1. All values calculated using IMS Health Incorporated Xponent™ general prescriber sample 2007 data, and population estimates from the US Census Bureau.

In both regressions, concentration is greater, other things equal, as population increases. However as in the earlier number of distinct molecules prescribed regressions, in all counties with

greater than 500,000 population physicians seem to exhibit similar levels of concentration. Female prescribers have more concentrated prescribing. Concentration is unaffected by practice size for overall antipsychotic prescriptions, however solo practitioners have more concentrated atypical antipsychotic use. DOs have less concentrated prescribing. Hospital-based physicians are no different from other physicians in their prescribing concentration behavior. Finally we observe that prescribers that place restrictions on the use of prescribing data for pharmaceutical marketing purposes have less concentrated prescribing; however this effect is only marginally significant.

D. Physician Deviant Prescribing Behavior

Finally we examine the deviation of any individual physician's prescribing behavior from national market shares, and from aggregate drug molecule shares in their HRR; we term this deviance from national averages and from HRR averages, respectively. Recall that because of possibly varying initial experience with an antipsychotic drug about which they attempted to learn more, our theoretical framework predicts greater deviance for low-volume prescribers, other things equal, as well as for others whose present value of benefits from learning regarding variety is lower. Results from both analyses are very similar and therefore we only report here the results that examine deviance from national market shares.

Initial visual examination of the deviation data again suggested a log normal distribution, hence we estimated a specification with log deviation as the dependent variable by least squares . Familiar patterns of results emerged in this regression, as is seen in Table 9. In particular, higher volume physician prescribing mimics national averages better than lower volume physician prescribing (i.e., low volume prescribers deviate more from national market averages). This pattern is particularly true for PCPs and for physicians coming from specialties classified as OTH, whose coefficient on the volume interaction variables are significantly negative. However, in contrast for PSY and NEU specialties deviation from national averages decreases less rapidly with volume -- the positive coefficient estimates

on the volume interaction variable largely offset the negative estimate on the (implicit) OTH-volume interaction variable. Holding volume fixed, PSY prescribers deviate the least, followed by PCPs and NEUs, each deviating less than OTH physicians (omitted group). Notably, the oldest quartile of physicians and female physicians are more deviant than younger and male physicians, respectively.

Table 9: Linear Regression on Log (Deviance in Physician Antipsychotic Prescribing from National Market Shares)

	Coefficient	**Standard Error**	**P>|z|**
Total Yearly Antipsychotic Prescriptions	-0.00131	0.00014	<.001
PCP*Total Yearly Antipsychotic Prescriptions	-0.00079	0.00016	<.001
PSY*Total Yearly Antipsychotic Prescriptions	0.00079	0.00014	<.001
NEU*Total Yearly Antipsychotic Prescriptions	0.00059	0.00022	0.008
Age Quartile 43-50*	-0.013	0.018	0.456
Age Quartile 51-58*	-0.007	0.018	0.674
Age Quartile 59+*	0.054	0.019	0.005
PCP*	-0.661	0.019	<.001
PSY*	-1.458	0.024	<.001
NEU*	-0.499	0.039	<.001
Female*	0.045	0.015	0.003
Population 150,000-500,000 (county)*	0.021	0.018	0.228
Population 500,000-1,000,000 (county)*	0.101	0.019	<.001
Population more than 1,000,000 (county)*	0.085	0.018	<.001
Solo Practice*	0.012	0.016	0.469
Hospital Based Physician*	0.025	0.023	0.283
DO Flag*	-0.036	0.023	0.110
Physician Opt Out*	-0.052	0.035	0.134
Constant	8.204	0.023	<.001
Number of Observations= 17,652			
R^2= 0.345			

*Indicates dummy variable. All values calculated using IMS Health Incorporated Xponent™ general prescriber sample 2007 data, and population estimates from the US Census Bureau.

Deviance from national market shares increases with the population of the county in which the physician practices (although this effect dissipates as physicians in counties with 500,000 + residents

have similar prescribing patterns), but is unaffected by size of office practice, whether the physicians is hospital based, and whether prescriber restricts release of prescribing data, and whether the physician has a DO or MD degree.

Finally, we have undertaken a number of robustness checks, mostly involving the relationships among concentration, specialty and volume. For example, to check whether our specialty-volume interaction term estimates in fact simply reflected a nonlinear, quadratic relationship in volume, we added a quadratic volume term. In another model we added quadratic volume interacted with specialty. In both cases, while some of the additional terms were statistically significant, the estimates on the volume-specialty terms were essentially unchanged. We also limited the sample just to the 3,463 psychiatrists. In that model, while the volume term had a significant negative coefficient estimate, it was very small; estimates on some of the other variables were statistically significant, but qualitative findings were essentially unchanged.

VII. DISCUSSION

In the Introduction we noted that this research builds on the insights and empirical findings reported by Frank and Zeckhauser [2007] regarding primary care physician "ready-to-wear" vs. "custom-made" treatment of patients. Our empirical analyses have both a wider range of physician specialty prescribers yet also a more focused treatment choice – antipsychotic drugs as maintenance treatments for schizophrenia and related chronic conditions. These findings largely complement and extend those reported by Frank and Zeckhauser.

Our empirical findings on regional disparities differ in large part from those reported by the Dartmouth Atlas project authors. As reported in Table 1, regional heterogeneity as measured by coefficients of variation considered to be high (above 0.4) occur in our antipsychotic concentration prescribing behavior only at the individual prescriber and county level of aggregation, but are low (less than 0.2) at the HRR and greater levels of geographical aggregation. To examine regional disparities in

greater detail, we have estimated regression equations with the prescriber's total 2007 volume of antipsychotic prescriptions (or its logarithm) as the dependent variable, and the set of non-volume explanatory variables specified in the tabled results as explanatory variables; we then estimate this equation with and without HRR fixed effects added, and examine how much additional explanatory power is provided by the HRR fixed effects. Although we find the 305 fixed effects are jointly highly significant, their incremental contribution to goodness of fit is *de minimus*. Specifically, for the volume levels regression, addition of 305 fixed effects increases the R^2 from 0.2622 to 0.2747 (a 4.8% proportional increase), while for the log volume specification the increase is from 0.3713 to 0.3855 (a 3.8% proportional increase). The variability in antipsychotic behavior that we observe is at the level of the individual prescriber, and this prescriber behavior is remarkably similar across HRRs and states.

We note that other researchers have recently reported that regional disparities are in some cases much less than the Medicare surgical and related procedures reported by the various Dartmouth Atlas collaborators. For example, Rettenmeier and Saving [2009] report that rankings of states on the basis of Medicare per enrollee health care spending differ substantially from those based on per capita health care spending on the non-Medicare/Medicaid population.

Zhang, Baicker and Newhouse [2010] examined annual 2007 inpatient, outpatient and pharmaceutical spending for 533,170 beneficiaries simultaneously enrolled in Medicare Part A and B, and in stand-alone Part D Medicare plans. They find that across the 306 HRRs pharmaceutical spending varies less than medical spending, and that pharmaceutical spending is only weakly positively correlated (r = 0.10, P=0.07) with medical (non-drug) spending, They interpret this weak correlation as being" consistent with drugs' being a substitute for medical care for some patients and a complement to medical care for others."[30] Alternatively, HRRs with high medical spending do not have offsetting lower pharmaceutical spending – they are not at all associated.

One recent article receiving much public attention highlighting the large geographic variations in Medicare medical care spending was that by Atul Gawande [2009], who compared Medicare spending in two nearby Texas cities, McAllen and El Paso, and found a nearly two-fold difference in per capita Medicare spending. Gawande attributed this discrepancy to a change in McAllen during the mid-1990s when health care providers apparently adopted a greater "entrepreneurial spirit" and a "culture of money". In response, since the same providers generally care for both Medicare and privately insured patients, Franzini, Mikhail and Skinner [2010] inquired whether, in the same two cities, similar patterns of care are observed for people under age 65. With several exceptions, Franzini et al. found that spending per capita for medical services by privately insured populations in McAllen and El Paso was much less divergent. For example, while spending per Medicare enrollee per year was 86% higher in McAllen than in El Paso, total spending per member per year was 7% lower in El Paso for the population insured by Blue Cross and Blue Shield of Texas. After examining and ruling out several other possibilities, Franzini et al. concluded that "health care providers respond quite differently to incentives in Medicare compared to those in private insurance plans."[31,32]

Our theoretical framework builds on a Bayesian learning model, in which a physician can only learn how to use a given drug effectively by prescribing that particular drug to patients, i.e., there is no possible learning about other drugs that the physician has not prescribed. While this framework can help explain persistent physician concentration prescribing behavior as the rational outcome based on learning from own prescribing behavior, and thereby be consistent with the Frank and Zeckhauser "sensible use of norms" behavior, our theoretical framework entirely ignores learning from others, spillovers, and herding behavior. Chandra and Staiger [2007] have developed and estimated a model that focuses on productivity spillovers related to local specialization in heart attack care, whereby excellence in one clinical approach in a local market raises the average skill of other practitioners of that approach operating in the same market. This in turn leads to greater specialization and reduces both

the absolute and relative productivity of practitioners using alternative approaches. Homogeneity in clinical approach within a geographic area, and substantial heterogeneity across areas, can reflect what may also be sensible and useful since they stem from positive spillover effects from local specialization. In future research, it would be useful to attempt to incorporate various types of spillover effects into physician prescribing behavior. This is particularly important, since learning from sources other than one own's prescribing behavior is a critical component in efforts to enhance the practice of evidence-based medicine.

VIII. SUMMARY AND DIRECTIONS FOR FUTURE RESEARCH

Our empirical analysis has revealed that several key patterns of findings. First, we observe that higher volume physician do in fact use a wider variety of drugs. This is true when we examine physicians' use of antipsychotics overall and when we focus only on their use of atypical antipsychotics. In addition we find that volume matters most for those physicians that are PCPs or that are trained in specialties that do not typically prescribe antipsychotics in large volumes, the OTH prescribers. In some analyses volume matters also for PSYs but in all regressions it matters less for PSY physicians than for other prescribers. We interpret this as medical specialty training experience and experience gained from high volume prescribing as being substitute sources of prescribing knowledge.[33]

We also observe that physicians in the middle of their career (those from 42-58) prescribe the widest variety of antipsychotic drugs whereas the oldest quartile of physicians tends to prescribe fewer of the newest drugs (atypicals); moreover, their prescribing patterns deviate more from national and HRR averages.

Somewhat surprisingly physicians practicing in smaller counties and those that have a DO instead of an MD degree prescribe a wider variety of antipsychotic and atypical molecules, have less concentrated prescribing behavior and deviate less from national averages.

The predictions from the theoretical model outlined in the earlier part of this manuscript help illuminate reasons why we observe these patterns of prescribing behavior. In particular, in a world where physicians are balancing the benefits of learning how to use a new drug with the costs of learning about these drugs, high volume physicians would tend to realize a greater return from exploration than would low volume prescribers. In addition, we would expect physicians closer to retirement to also have less of an incentive to prescribe a wide variety of drugs, since their future patient volume benefiting from this knowledge is smaller, other things equal.

Finally, we observe that PSYs use the widest variety of drugs and that volume is not a strong predictor of their prescribing behavior. If these physicians in their specialty training learned how to treat patients with schizophrenia using these drugs more effectively, then we may expect these physicians to become adept at prescribing these drugs earlier in their careers. Therefore their costs of learning would be lower and this would help explain why even low volume psychiatrists prescribe a wide variety of antipsychotics and atypicals. Another interpretation of this finding is that psychiatrists see a wider range of patients and therefore these physicians' patients benefit more from being prescribed the drug that is best suited to their particular symptoms, even if the physician is not adept at managing the side effects that result from the prescribed drug. We cannot differentiate between these two explanations without having data on patients.

A major limitation of this study is that we do not observe data on the patient populations treated by physicians. However, we note the literature cited and results obtained by Frank and Zeckhauser [2007] suggest that other than through demographics, variations in patient condition severity and clinical manifestations are remarkably unrelated to physician practice behavior, and that results obtained by them are largely quantitatively unaffected with alternative specifications incorporating patient-specific data. The dominant role of physicians over patients in influencing choice of medication has also been reported elsewhere both by other health economists (e.g., Hellerstein

[1997] and Zhang, Baicker and Newhouse [2010]) and by academic clinicians (e.g., Schneeweis, Glynn, Avorn and Solomon [2005]).

Several interesting future research projects have emerged from our study. As noted earlier, the relative efficacy, tolerability and cost-effectiveness of the various typical and atypical antipsychotics remains a controversial issue, even after publication of a substantial number of articles over the last decade, including those based on randomized clinical trials.[34] What is less controversial is that this controversy has had a substantial impact on changing prescription shares of the various antipsychotics. Our IMS Health data reveal that between 2002 and 2008, the Seroquel prescription share increased from 21% to 37%, Abilify from 0% to 16%, Geodon from 4% to 7%, even as the Risperdal share declined from 35% to 26%, and that of Zyprexa from 34% to 12%. Who were the prescribers who switched most rapidly – low or high volume, what specialties, gender, age group – and who were those who changed relatively little? What were the relative responses to the FDA issuing bold boxed warnings, to professional associations revising treatment guidelines, to publication of major findings in medical journals? Understanding which prescribers, and their characteristics, respond most and which the least would provide valuable information to guide future information dissemination strategies.[35]

Our findings suggest that a significant proportion of the heterogeneity in the treatments patients receive depends upon physician preferences in treatment regime. It would be informative and useful to identify specific patterns in physician decision-making that appear to indicate general differences in "style" across physician practices, analogous to recent investigations characterizing management style.[36]

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ENDNOTES

[1] These are the terms used by Frank and Zeckhauser [2007].
[2] Also see Cosccelli [2000], Coscelli and Shum [2004] and Crawford and Shum [2005].
[3] Frank-Zeckhauser [2007], pp. 1125-6.
[4] It also builds on the framework outlined by Phelps and Mooney [1993] and Phelps [1992,2000].
[5] Mosby's Medical, Nursing, & Allied Health Dictionary [1998], p. 1456.
[6] Domino, Norton, Morrissey and Thakur [2004].
[7] American Psychiatric Association [2004], p. 9.
[8] Duggan [2005].
[9] Frank, Berndt, Busch and Lehman [2004].
[10] American Psychiatric Association [2004], p. 66.
[11] Additional controversy emerged when major studies, published in 2005 and 2006, raised issues regarding whether there were any significant efficacy and tolerability differences between the costly SGAs and the older off-patent conventional antipsychotics, as well as differences among the five SGAs. Important issues regarding the statistical power of these studies to detect differences, were they present, have also been raised, and currently whether there are any significant differences among and between the conventional and SGA antipsychotics remains controversial and unresolved. For further details and references, see the Appendix available from the lead author, "Timelines – U.S. Food and Drug Administration Approvals and Indications, and Significant Events Concerning Antipsychotic Drugs".
[12] Although at times we will use the words "prescribed", "written" and "dispensed" interchangeably, the IMS Health Xponent data are based on dispensed prescriptions; for a variety of reasons, a physician can prescribe a Product X but it may not be dispensed at all, or in fact after consulting with the prescriber the pharmacist may dispense product Y.
[13] The 75% cutoff is a stringent one, for the patient population seen by a prescriber is likely somewhat heterogeneous, with some patients having failed to respond to various medicines (perhaps including the physician's favorite one), and others having a history of effective response to another drug. For the latter, a physician may be reluctant to switch from an effective drug to the physician's favorite one, given the medical profession's adage "Don't shoot a singing bird".
[14] See, for example, Skinner and Fisher [1997], Fisher, Wennberg, Stukel et al. [2003a,b] and Yasaitis, Fisher, Skinner et al. [2009].
[15] For further details, see Dartmouth Atlas Project.
[16] The U.S. Department of Justice horizontal merger guidelines state that when a merger results in a change in the HHI of more than 100 points and with the merged firm generating a post-merger industry HHI of > 1800, the merger will be presumed to create or enhance market power or facilitate its exercise, and will likely be very closely scrutinized by the Department of Justice, and perhaps even challenged. The merger guidelines can be accessed online at http://www.justice.gov/atr/public/guidelines/horiz_book/15.html.
[17] For example, if a prescriber only used three of the atypicals with prescription shares of 65%, 25% and 10%, the HHI would be 4950; if however, all six were used equally (each 16.67%), the HHI would be 1667.33.,
[18] This framework is summarized in Gibbons and Henderson [2011].
[19] An early discussion of these principal-agent issues is found in Pauly [1980], albeit in the context of hospital treatments, not pharmaceuticals.
[20] For discussion, see Frank and Glied [2006] and Huskamp [2003].

[21] See Banerjee [1992] and Bikhchandani, Hirschleifer and Welch [1992].
[22] In preliminary data analyses examining relative antipsychotic prescribing by specialty, nurse practitioners were the fourth largest specialty, comprising 20,872 of the 224,259 (9.3%) prescribers in the top eleven specialties.
[23] For further details, see, for example, Cipher and Hooker [2006]; also see Hooker and Cipher [2005], Morgan and Hooker [2010], Pohl, Hanson, Newland and Cronenwett [2010] and Shell [2001].
[24] In addition to excluding the 1,641 non-physician prescribers, we dropped 237 observations for which county codes were missing, seven with missing gender information, and three observations for which age information was an unreasonable outlier. This left us with a total of 17,652 observations.
[25] In a Physician Sample appendix, available from the lead author, we discuss this later point in more detail.
[26] Alternative measures of concentration that account explicitly for inherently "noisy" concentration from low volume prescribers have been developed by Ellison and Glaeser [1997] in the context of the geographic concentration of manufacturing industries, and adapted to the context of prescription pharmaceuticals by Stern and Trajtenberg [1998]. Our deviance measure is closely related to the Ellison-Glaeser concept.
[27] For 214 of the physicians information about the size of the county in which they practice is not available, and they are therefore excluded in our later analyses. This reduces our final sample size to 17,652 physicians.
[28] DO is doctor of osteopathy. Mosby's Medical Dictionary [1998, p. 1169] defines osteopathy as "a therapeutic approach to the practice of medicine that uses all the usual forms of medical diagnosis and therapy, including drugs, surgery, and radiation, but that places greater emphasis on the influence of the relationship between the organs and the musculoskeletal system than traditional medicine does. Osteopathic physicians recognize and correct structural problems using manipulation."
[29] We remind the reader that we are using the word "prescribed" somewhat loosely, for in fact the Xponent data only track the number of prescriptions dispensed via retail and mail order. The number of prescriptions written may deviate from the number actually dispensed for various reasons, which we do not examine here.
[30] Zhang, Baicker and Newhouse [2010], p. 407.
[31] Franzini, Mikhail and Skinner [2010], p. 2302.
[32] Related findings have been reported by Philipson, Lockwood, Goldman et al. [2010], who find that variation in utilization in the public sector is about 2.8 times as great for outpatient visits ($P < 0.01$) and 3.9 times as great for hospital days ($P = 0.09$) as in the private sector. However, in part because of government monopsony power, variation in spending appears to be greater in the private sector, consistent with the importance of public sector price restraints.
[33] In a related finding, Doyle, Ewer and Wagner [2008] find that while treating randomized patients at the same hospital, medical residents from a lower-ranked medical school were able to substitute diagnostic tests and specialist consultation for the more rapid judgments made by residents from a higher-ranked medical school, achieving the same outcomes on average but at a higher cost.
[34] An appendix to this paper available from the lead author, "Timelines Appendix" provides further details. Among the more notable publications are those based on the CATIE study; see, for example, Lieberman, Stroup, McEvoy et al. [2005], White [2006] and Kraemer, Glick and Klein [2009].
[35] The only research on this topic of which we are aware is that by Hoblyn, Noda, Yesavage et al. [2006].
[36] See, for example, Bertrand-Schoar [2003] and Kaplan, Klebanov and Sorensen [2008].