Physician vs. Patient Incentives in Prescription Drug Choice

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Abstract

In response to rising health spending, public and private insurers use two mechanisms to direct spending toward more valuable treatments: "demand-side" incentives, which impose costs on the patient to limit moral hazard, and "supply-side" incentives, which adjust the physician's compensation to discourage spending. Using variation in patients' and physicians' exposure to incentives, I identify important differences in cost and health outcomes under these two mechanisms. Demand-side cost-sharing discourages both initial treatment and later adherence. Payment reforms drive physicians to substitute drug care and specialist referrals for office visits. I discuss the implications of these outcomes for optimal insurance design.

Keywords: physician agency, capitation, health insurance design

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1 Introduction

Annual health spending in the United States rose from $256 billion in 1980 to nearly $2.9 trillion in 2013, accounting for over 17% of the Gross Domestic Product.[1] In response, insurers and policymakers have designed incentives to steer this spending toward only the most cost-effective medical interventions. The incentives focus broadly on two conflicts that arise in the market for medical care. On the demand side, many patients purchase insurance against health risks. Facing only a small fraction of the cost of their care, patients may demand relatively expensive treatments. On the supply side, because patients lack the training to diagnose and treat their own condition, they must employ physicians to oversee their care. The physician, however, has her own private interests and may favor more intensive interventions. Both conflicts drive increases in spending.

I compare the effects of two categories of incentives intended to address these conflicts: "demand-side" incentives that affect the patient's negotiation with his physician and "supply-side" incentives that govern the transaction between the physician and insurer. The goal is to inform a key policy question: what set of incentives best limit the short-run costs from demand and supply-side conflicts without harming long-run patient health? Typical incentive schemes in this setting only correlate imperfectly with the insurer's long-run objective, and so they create trade-offs for designers of an incentive program (Baker (1992) and Lazear (2000)). For example, in response to strong demand-side cost sharing, patients may fail to adhere to their prescribed treatment, decreasing the likelihood of recovery and increasing the rate of relapse. With the greater demand for follow-up care, long-run costs to the insurer may actually increase. Stronger supply-side incentives, by discouraging repeated physician-patient interactions, can have two effects. First, they may lead to substitution away from office-based care and toward drug care. Drug treatment may lead to poorer health outcomes relative to more intensive interventions. Second, amongst the set of drug options, supply incentives may discourage use of those options that require more physician involvement to tailor the treatment. If more tailored treatments produce better health, these incentives may worsen patient outcomes.

I describe a simple model of the patient-physician interaction, similar to the approach of Pauly (1980) and Dranove (1988), to provide precise hypotheses about the

[1] Source: Centers for Medicare and Medicaid Services, Office of the Actuary, National Health Statistics Group, 2013.

effects of patient and physician-directed incentives on treatment decisions. I then test these hypotheses using data on treatment choices for patients suffering from depression. I choose this setting for two reasons. First, depression care is common in the United States, as major depression affects 6.5% of adults in the US each year. In 2008, patients filled 164 million monthly prescriptions in the antidepressant class; only cholesterol treatments and pain medicines exceeded this level of sales.[2] Second, for depression diagnoses, physicians choose among multiple treatment options, including office-based psychotherapy and a large set of prescription drugs. The American Psychiatric Association's practice guideline lists 26 unique drug compounds approved for depression treatment, with no single drug proven superior in efficacy (Karasu et al. (2000)). Physicians thus exercise significant discretion in prescribing treatments, leaving opportunity for various incentives to operate.

I motivate the empirical analysis with a comparison of treatment choices in the raw data. I compare patients whose plans use different financial incentives, including Preferred Provider Organization (PPO) plans that pay physicians per visit as well as two types of Health Maintenance Organizations (HMOs). The first HMO plan type places restrictions on the network of providers an enrollee can visit but still pays those physicians per visit; the second HMO type uses similar network restrictions but pays primary care physicians using capitation contracts. Capitation contracts provide an up-front payment to physicians for every patient assigned to their practice, regardless of the patient's actual health care use. I find important differences across plan types in the use of specialty care and in the choice of drug treatment. Patients with the least restrictive PPO plans that pay physicians per visit receive psychotherapy at a rate of 8%. Strikingly, for patients in HMOs that pay physicians via capitation, the rate of psychotherapy is even higher, at nearly 12%. When physicians prescribe medications, those treating PPO patients select particular branded medications. In contrast, for patients in HMOs that pay physicians via capitation, physicians substitute fluoxetine, a generic drug, for branded treatments. Capitated patients receive fluoxetine at a rate of 18%, a full 10 percentage points higher than patients with either HMO or PPO plans that pay physicians per visit. The distinct prescribing patterns for capitated patients remain even when one examines the data within a region of the country and when controlling for observable patient characteristics.

Given these patterns in the raw data, I develop an empirical framework to explore

[2] "Top Therapeutic Classes by US Sales", *IMS National Sales Perspectives*. IMS Health, 2008.

the likely mechanisms behind these findings and to measure the effect of insurance design on both costs and health. While patients are not randomly assigned to insurance plans in my setting, several features of the data provide useful variation in the incentives patients face. First, in the time span of the data, patient cost-sharing changed substantially across nearly all regions. Cost-sharing increased for both branded and generic treatments, and for two new treatments that entered the market during the sample period. Thus, patients diagnosed with depression at different points in time face different cost sharing regimes, independent of their illness profile. Second, I use the richness of the individual-level claims data to address concerns that patients select into insurance plans based on the cost of their depression treatment. Specifically, I restrict my analysis to only those patients newly diagnosed with depression. New patients are unlikely to have chosen their original insurance plan as a function of the specific depression treatment prescribed to them at the time of diagnosis. I also collect insurance claims data for diagnoses outside of depression to calculate a measure of each patient's health, the Charlson comorbidity index, developed by Charlson et al. (1987). I include this index in the choice model to control for the possibility that patients with multiple illnesses select into plans with overall lower out-of-pocket costs, including for depression medications. Finally, third, I use rich insurance plan characteristics available in the data to control for plan types. Thus, in my analyses I compare the treatment outcomes of patients with similar illness profiles and with broadly similar insurance plans that differ only in the physician incentive scheme applied. Importantly, the payment scheme itself is rarely published in plan materials for consumers, and so is unlikely itself to serve as a characteristic that drives consumer enrollment in a plan.

To compare the effect of multiple incentives on costs, I first estimate a flexible choice model that permits unobserved heterogeneity in physician and patient preferences over price. I use a control function approach to handle the potential endogeneity of the insurer's price. The results amplify the findings in the preliminary analyses: promoting generic drugs by lowering their relative copayments, holding other incentives fixed, prompts an increase in the share of generics from 28% to 35%. The change represents an average own-price elasticity of between -.3 and -.5, within the range of previous estimates identified in experimental and cross-sectional studies.[3] Greater copayment rates have no significant effect on the rate of psychotherapy prescribed.

The response of patients to copayment incentives seems uncontroversial and follows

[3]See Goldman et al. (2007) for a review of the literature on prescription drug cost-sharing.

the pattern in a long literature in health economics.[4] The response of physicians to supply-side policies requires more analysis; relatively little empirical work examines the effect of supply-side incentives, particularly their effect on prescription drug care.[5]

I examine both the margin of broad treatment type– drug therapy, psychotherapy, and no therapy– and the choice of specific drug therapy for those patients prescribed medications. For the choice of treatment type, I find that primary care physicians facing capitation elect psychotherapy treatment at higher rates. Specifically, I compare patients in non-capitated HMOs with patients in capitated HMOs to isolate the effect of the payment mechanism. In this comparison, I find that patients in capitated HMO plans receive formal treatment 2.8 percentage points more often. Patients of capitated primary care physicians receive psychotherapy alone at a rate of 1.1%, an increase of .86 percentage points (75%) above the rate of psychotherapy provided to patients of non-capitated primary care physicians.[6]

For drug choice, the choice model estimates imply physicians paid under capitation choose less expensive drugs. Switching all patients to capitated plans, for example, would increase the share of generics prescribed from 28% to 38%. The specific generic treatments predicted to gain the largest share under capitation are those that, all else equal, generate the lowest rates of switching in the panel data. Thus, I infer that financial incentives drive capitated physicians to choose treatments that require fewer follow-up visits. Alternatively, one could interpret the empirical findings as evidence that physicians who enter into capitation contracts have underlying preferences for cost containment. To investigate this alternative hypothesis, I examine auxiliary physician-level survey data to augment my patient-level data. Among other questions about the physician's practice, the surveyors ask whether the physician accepts capitation for any of the patients she treats and also ask for the share of the physician's patient population that is insured under managed care plans, like HMOs. I use these survey variables to test the physician selection hypothesis. Under this hypothesis, the drug shares for those doctors who have ever accepted capitated payments would be different from those who have not, particularly on the cost dimension. In this analysis, I control

[4]See, for example, Aronsson et al. (2001), Foo and Cullen (2012), Gaynor et al. (2007), Hellerstein (1998), Huskamp et al. (2005), Nair et al. (2003), and Shrank et al. (2007).

[5]Armour et al. (2001), Bloom et al. (2002), and Ho and Pakes (2013) measure the effect of supply-side incentives on aggregate health spending and on the costs of inpatient care. Limbrock (2011) examines the effect of managed care incentives in the prescription drug market.

[6]This share includes patients initially diagnosed with depression in a primary care office visit but treated using psychotherapy by other providers, including psychiatrists, within 3 months of the initial diagnoses.

for the physician's specialty and practice mix, including the share of her practice revenue that comes from private insurance and from managed care plans. Contrary to the prediction of the physician selection hypothesis, I find the drug shares to be statistically indistinguishable across these two groups.

Finally, I evaluate the relative effect of supply and demand-side incentives on health in the panel data. I start with a duration analysis, estimating a piecewise-constant proportional hazard model of the time to exit from treatment. I find adherence rates differ across plan types and copayment incentives, conditional on the drug chosen. Patients enrolled in non-capitated HMO plans and plans with high degrees of cost-sharing have the poorest rates of adherence. Capitated HMO patients have rates of adherence above other HMO patients and only slightly below those of PPO patients. The lower rates of adherence under both HMO and demand-side incentives translates into lower recovery rates. Results from Berndt et al. (2002) suggest that, compared to patients who take the latest generation antidepressants for more than 1 month, those patients who quit within one month have an eight percentage point lower probability of full remission and a 15 percentage point lower probability of partial remission within four months of diagnosis.

I use the panel data to develop a second health outcome measure. I look for evidence of differential rates of relapse in the period 3-6 months after the initial episode as a function of plan characteristics. Controlling for patient and physician attributes and the length of the initial treatment episode, I find relapse increases slightly with capitation, from 5.4 to 5.8%. Demand-side cost-sharing produces a larger increase in relapse, depending on the level of cost-sharing. That adherence and health decline with stronger incentives, particularly demand-side incentives, suggests a trade-off in treating chronic conditions; minimizing long-run costs may require weaker incentives than those employed for acute conditions. For diseases, like depression, for which adherence strongly influences long-run health, insurers may improve outcomes by employing capitation rather than greater cost-sharing.

I proceed in the paper as follows. In Section 2, I provide a model of the patient-physician interaction, demonstrating the potential for conflict and the role of insurer incentives in this relationship. I then test the model's hypotheses in an empirical setting. I describe the data and motivate the empirical model in Sections 3 and 4. I analyze the static relationship between incentives and costs in Section 5 and the dynamic relationship between incentives and health in Section 6. Finally, in Section 7, I discuss the implications for optimal insurance design. Section 8 concludes.

2 Model of the Patient-Physician Interaction

I model the physician's selection of drug treatment for an ill patient to illustrate the potential for conflict. The asymmetry in information between the trained physician and the patient gives the physician authority to recommend a treatment that is privately optimal but may not maximize the patient's outcome.

I describe a special case in which the patient's health falls into one of two states: θ_S or θ_M, where θ_S represents a severe illness and θ_M a mild illness. To treat the illness, the physician can recommend one of two treatments. The first, d_H, is a high-cost blockbuster drug, while the second, d_L, is a low-cost drug.[7] From the patient's perspective, the low-cost drug, d_L, is preferable for a mild illness; d_H is preferable for a severe illness. Formally, I assume the patient's utility takes the following linear form:

$$U_j^{Patient}(\theta_k) = Y_{jk} - C_j \tag{1}$$

Here, the patient suffers from illness k and consumes treatment j. The patient's utility depends on: (1) Y_{jk}, a measure of both the efficacy and tolerability of drug j for patients of illness type θ_k, and (2) the out-of-pocket cost for the drug, C_j.

When the patient feels ill, he cannot determine his illness type to select the appropriate treatment. He therefore visits a trained physician. The physician does not face the costs of the treatment but may have private benefits from a particular choice. For example, if the physician has prescribed treatment j for many patients in the past, she'll save the costs of researching the proper dosing levels. Her utility depends on her own private benefits, b_j^k, which may vary by illness type k, as well as weighted consideration for the patient's utility:

$$U_j^{Phys}(\theta_k) = b_j^k + \gamma(Y_{jk} - C_j) \tag{2}$$

Through the altruism term, $\gamma(Y_{jk} - C_j)$, the physician accounts for the patient's treatment outcome and drug costs. Physicians may differ in their degree of altruism, with each having a distinct level of γ.

To illustrate the main features of the model in this special case, I make four simplifying assumptions. First, $C_H > C_L$; corresponding to the label, costs for d_H exceed those for the low-cost alternative, d_L. Second, I assume the physician always receives higher private benefits under the blockbuster drug, d_H, independent of the patient's

[7] I use drugs for clarity of exposition; one of the treatments could instead represent an office-based treatment.

illness. Third, I let $E(Y_H^S) > E(Y_L^S)$ and $E(Y_H^S - Y_L^S) > C_H - C_L > 0$. In the severe illness state, treatment d_H is more effective on average than d_L. The blockbuster drug, d_H, is also more costly, but the value of the increased effectiveness exceeds the added cost. Finally, fourth, I let $E(Y_L^M) \geq E(Y_H^M)$. For mild illnesses, treatment d_L is weakly more effective than d_H.

The antidepressant class matches the assumptions of this special case. Several low-cost treatments outperform new patented alternatives for mildly-ill patients. In eight studies reported by Gartlehner et al. (2007), Effexor (venlafaxine), a popular new medication, produced a larger treatment effect for patients suffering from major depression relative to existing products; for less severe conditions, there was no strong evidence of improved efficacy. However, patients on Effexor reported a 10% higher incidence of nausea and vomiting relative to existing treatments.

With this simplified setting, I describe the treatment selections that will result in each of the illness states.

2.1 One Period Model

In the severe case, both the patient and physician prefer the high-cost drug, d_H. It is more effective on average, and the better expected outcome exceeds the added out-of-pocket costs. In the mild case, there is potential for disagreement. If the patient could diagnose his own mild condition, he would prefer the low-cost drug. The physician will recommend the low-cost drug if and only if her sensitivity to patient outcomes, γ, satisfies the following inequality:

$$E(U_H^{Phys}(\theta_M)) < E(U_L^{Phys}(\theta_M)) \Leftrightarrow \quad (3)$$

$$\frac{b_H - b_L}{E(Y_L^M - Y_H^M) + (C_H - C_L)} < \gamma \Leftrightarrow \quad (4)$$

When (1) the low-cost drug is more effective, (2) the blockbuster drug is far more expensive than the low-cost drug, and (3) $(b_H - b_L)$ is small, the inequality is easier to sustain. That is, even physicians with low values of γ will prescribe the patient's preferred option.[8]

[8]In this setting, there is a simple mechanism to ensure the physician chooses d_L when the patient suffers from a mild illness: pay a lump sum transfer to the physician of $(b_H - b_L)$ whenever she prescribes the low-cost drug. With this transfer, the physician receives b_H in either state. The inequality in (4) becomes $\gamma > 0$ and the patient and physician preferences align. This first-best scheme fails in practice because the level of the required payment is often unknown or prohibitively costly.

2.2 Two Period Model

To illustrate the role of capitation in treatment choice, I extend the simple example to two periods. Under capitation, the physician faces an additional cost, S, if the patient returns for a follow-up visit in the second period. These costs place additional liability on the physician's initial treatment choice. In a two-period world, even less altruistic physicians select the patient's preferred choice.

To see this, consider a slight change to the two drug setting. After realizing outcomes under drug d_L or d_H in period 1, patients return early to the physician for consultation if they experience a poor outcome.[9] I denote the probability of an early reassessment and switch as p_H when the physician chooses the high-cost drug initially and p_L when the physician (correctly) chooses the low-cost drug for a mild illness. In the case of early reassessments or illness relapse, the physician faces an additional pecuniary or non-pecuniary cost, S:

$$U_j^{Phys}(.) = b_j + \gamma(Y_j - C_j) - S$$

The physician's utility depends on her private benefits, the patient's utility, and S.

As in the one period example, there is a conflict when the patient suffers from a mild illness. The expected outcome for the patient in the mild case, net of costs, is higher under the low-cost treatment. The forward-looking physician will prescribe the low-cost drug if the inequality below holds:

$$E(U_L^{Phys} + U_j^{Phys}) \quad > \quad E(U_H^{Phys} + U_j^{Phys}) \tag{5}$$

where U_j^{Phys} is the physician's utility under a second period choice, j. Substituting in for the expected utilities in (5) and rearranging:

$$\gamma > \frac{(b_H - b_L)}{E(Y_L^M - Y_H^M) + (C_H - C_L)} - \frac{S * (p_H - p_L)}{(E(Y_L^M - Y_H^M) + (C_H - C_L)) * (2 - p_H - p_L)} \tag{6}$$

Compared to the inequality from the one-period case, the expression in (6) contains a second term. When S, the cost to the physician from a reassessment, is greater than zero and when $p_H > p_L$, this second term is strictly positive. In this case, the two-period

[9]Specifically, patients will return if the outcome causes them to update their prior beliefs on the quality of the drug sampled such that its expected utility falls below the expected utility of the alternative.

inequality is easier to sustain for a given γ. When reassessments are costless or when the initial choice doesn't change the likelihood of a patient complaint, the two-period model is identical to the one-period version.

I apply the insights from this simple two treatment example to the setting of antidepressant choice. Specifically, I test whether increasing the gap in patient copayments between treatments leads physicians to prescribe more cost-effective drugs; I consider the effect of changes in HMO design, which can alter the physician's relative private benefits from treatments; and, I examine how capitation might encourage better initial matching to avoid treatment reassessments.

3 Data

To estimate the effects of demand and supply-side incentives, I employ health insurance claims data available from Thomson Reuters' MarketScan databases. I obtain data for 2003-2005 from the *Commercial Claims and Encounters* database, which contains patient level clinical utilization, expenditure, and enrollment data for inpatient, outpatient, and prescription drug services. I link this data to patient demographics and to plan design features from the *Benefit Plan Design* database.[10] The individuals recorded in the data include active employees working for a group of large US firms that contract with one of 100 participating payers; the employees' dependents and some classes of retirees enter the database as well.

I collect a sample of patients diagnosed in an outpatient office visit with one of five categories of depression diagnoses: major depression; dysthymia and depression with anxiety; prolonged depressive reaction; adjustment disorder with depressed mood; and, depression not otherwise specified.[11] Conditioning on observed diagnoses rather than observed prescriptions provides three benefits: (1) I can focus on more severe depression categories for which formal guidelines recommend medical intervention, (2) I can examine the extensive margin choice of no treatment vs. either drug treatment or psychotherapy and (3) I avoid episodes involving off-label use of antidepressants. However, by requiring that the patient receive a depression diagnosis, I may miss individuals in the broader dataset who do not receive a formal diagnosis but may suffer

[10]Thomson Reuters MarketScan Research Databases. Ann Arbor, MI: 2003-2005.

[11]The depression diagnoses listed match the International Classification of Diseases (ICD-9-CM) codes of: 296.2, 296.3, 300.4, 309.0, 309.1, and 311. Melfi et al. (1998), Pomerantz et al. (2004), and Akincigil et al. (2007) use similar diagnostic codes in selecting a sample of depression patients.

from depression.[12]

I impose the following conditions on patient backgrounds to form an appropriate sample: patients cannot have a concurrent diagnosis of bipolar disorder or schizophrenia or receive drugs that signal these conditions, as these illnesses require distinct treatments[13]; the patients' age must fall between 18 and 64, the range for which the data are complete; patients must visit a health professional with the ability to prescribe drug treatments; and patients must not be pregnant, a condition that raises safety concerns for many of the treatments. I eliminate individuals dispensed medications within the first six months of data, since the illness could be pre-existing. In such cases, I would mistakenly interpret a second or third treatment choice as the initial decision. For the purposes of this static choice model, I restrict the analysis to the first prescription filled after the patient's initial depression diagnosis.[14] I use the patient's entire episode of treatment for the duration model estimation. The initial filters lead to a dataset of 98,112 unique patients observed between July 2003 through December 2005.

The data include background variables specific to the individual: (1) patient demographics, including age, gender, county of residence, and diagnosis; (2) the specialty of the treating physician; and, (3) characteristics of the patient's insurance plan, including the required copayments. The MarketScan data also include a plan-specific "ingredient cost" for each drug, which is the insurer's cost excluding the dispensing fee, sales tax, and rebates from the drug manufacturer. I supplement this data on drug prices with information on each drug's average side effects, dosing, and efficacy from psychiatry textbooks, clinical practice guidelines, and a meta-analysis of published clinical trials.[15] From the MarketScan data, I also record whether a patient's episode contains any claims for psychotherapy treatment during the period. Finally, I collect county-level information on reported wages, dividends, and interest income using the U.S. Internal Revenue Service's Statistics of Income for the 2005 tax year. I match this data to the county reported in a patient's record.

[12]Davidson and Meltzer-Brody (1999) discuss the widespread under-recognition and under-treatment of depression, particularly in primary care settings.

[13]Patients excluded due to comorbidities have a diagnosis in one of the following classes: bipolar and manic disorders (ICD-9-CM 296.0, 296.1, 296.4-.8) and schizophrenic disorders (ICD-9-CM 295.0-295.9).

[14]A literature in health economics models the drug treatment decision as dynamic, including Ching (2010), Crawford and Shum (2005), and Dickstein (2014). To address the main research questions in this paper, I abstract from these dynamic considerations in the treatment choice model. I do, however, use the panel nature of the data when measuring changes to patient health.

[15]See Murphy et al. (2009), Karasu et al. (2000), and Gartlehner et al. (2007).

Table 1 contains summary statistics on the individual-level covariates and drug product characteristics. Of the unique enrollees, 44% visit general practitioners, 28% visit a psychiatrist, and 28% visit other specialists, such as obstetricians. 28% suffer from major depressive disorder, the most severe diagnosis in the depression hierarchy. Women compose 71% of the observed sample diagnosed with depression. Of the plan types, capitated health maintenance organizations (HMOs) cover 35% of patients in the sample; non-capitated HMOs cover 13%; and other non-capitated plans, including preferred provider organizations (PPOs), cover the remaining 52% of patients.

The plan type categorical variable plays an important role in the analysis. In Table 2, I list the types of incentives commonly employed by each plan category, including whether the plan uses drug formulary tiers, utilization review, and pre-certification requirements for inpatient care. Capitated and non-capitated HMO plans, as defined by the database, differ in that capitated plans pay general practitioners for outpatient care using lump-sum payments rather than reimbursing physicians for each visit or procedure. These contracts also typically include "shared risk arrangements" under which the physician or physician group shares in any savings in total spending, including inpatient care, relative to a target level.[16] I offer evidence that capitated plans in my setting indeed employ such payment schemes by looking at the prevalence of specific complementary incentives in the plan-level data. Crucially, the two types of HMOs both employ stricter drug formularies relative to PPOs. The HMO plans differ in that the capitated HMOs rarely employ utilization review and case management. In practice, there is little need for explicit utilization review if payment incentives cause capitated physicians to internalize the cost of inpatient care.

In addition, I use the observed prescribing and prices within each plan to examine the formulary structure used. In particular, I check whether, across the 333 unique plan and year combinations, there is evidence of strict 'step therapy' formulary regulation in which the insurer requires the prescribing physician to begin treatment on a particular medication. I calculate, by plan and year, the market share for each drug in the antidepressant choice set, for prescriptions written for newly diagnosed patients. I calculate these shares only for the population of patients that receives drug care on the first visit. I then identify the maximum share across all drugs for each plan and year.

Across all plans, the median plan has a maximum share of 23.1%. The 95th percentile of the maximum share across all plans and years is 35.7%. These shares are

[16]See Ho and Pakes (2013) for an analysis of the effect of capitation on physicians' inpatient hospital referrals.

slightly larger than the overall shares by drug taken across plans, but are far below 100% or even 50%. It does not appear that the plans in the sample enforce a strict step therapy that limits the physician's ability to prescribe a range of drug options at the patient's first visit.

In the sample period, physicians choose between 19 medication options. Market shares and prices for the most common medications appear in Panel 1 of Table 1. The psychotherapy share reported in this table includes only those patients who received psychotherapy but no drug care; if a patient received both, his treatment would contribute to the relevant share of the drug he filled.

The average prices in Table 1 illustrate that patient copayments have been increasing over time for nearly all products.[17] The insurer costs change over time differentially by drug but also differentially by plan. The coefficient of variation in the insurer costs across plans varies from .05 to over .5 for several off-patent treatments and has been steadily rising over time in the sample data. I exploit this variation in the empirical model. In addition, two drugs entered in 2004, the center of my sample period: citalopram, the generic version of Celexa, and a new branded treatment, Cymbalta.

4 Empirical Motivation

To motivate a detailed study of the physician's choice behavior, I first present correlations between insurer-designed incentives and the choice of antidepressant treatment. In Table 3, I present the distribution of drug choices conditional on supply-side incentives. Because I use insurance claims data, I only observe prescriptions actually filled. If a patient received a prescription for an antidepressant during an office visit but never filled it, that patient would fall into the 'none' treatment share.[18] I separate out the share of individuals who receive only psychotherapy according to the insurance record. In Table 3, individuals receiving both psychotherapy and an antidepressant fall into the share for the relevant drug treatment.

[17] To carry out the later discrete choice analysis, I need to collect the plan-specific prices patients face for all the drugs in their choice set. Unfortunately, the Marketscan data does not provide this directly. Instead, it identifies only the tier structure each plan uses for its formulary and the level of the copayments by tier. I combine this information with the observed prices for all patients treated under the same insurance plan to construct the vector of prices a patient faces for his choice set.

[18] Similarly, if the physician offered the patient a free sample of a drug, that sample would not contribute to that drug's share unless the patient filled a new prescription for it at a pharmacy within three months of his initial office visit.

From the observed shares, it is clear that, unconditionally, patients treated under HMO plans that offer capitation contracts receive a far different distribution of drugs than those patients treated under PPOs or non-capitated HMOs. Capitated physicians use generics at a rate of 36%, 13 percentage points more than physicians paid by non-capitated HMOs and 23 percentage points more than physicians treating patients under PPO plans. On the extensive margin, the unconditional shares in Figure 1 illustrate that supply-side incentives affect the broad category choices of (1) no treatment, (2) branded drugs only, (3) generic drugs only, and (4) psychotherapy, both with and without concurrent prescription drug use. Comparing across HMO plans, those that pay primary care physicians via capitation show much greater use of psychotherapy to treat depression patients: the rate of psychotherapy treatments is 11.5% in capitated HMOs, vs. 2.1% for non-capitated HMOs. As a comparison, patients on the least restrictive PPO plans in the private insurance data use psychotherapy for the depression diagnoses I study at a rate of only 8%.[19]

These patterns persist even after controlling for a rich set of patient background characteristics.[20] In a logit framework, I condition on patient gender, patient age summarized into five blocks, the patient's diagnosis, the physician's specialty, the average income in the patient's home county, whether the patient lives in a metropolitan area (as defined by the US Census Bureau), the patient's home region, various attributes of the patient's plan, and also whether the patient lives in a state where the law requires pharmacists to dispense generic drugs when possible.[21] Holding these observables constant, physicians with incentives under capitation prescribe far more generics. In Panel 1 of Table 4, the generic share is roughly 14% higher under capitated HMOs relative to either PPO plans without capitation or HMO plans without capitation. In Panel 2 of Table 4, when patients face cost-sharing, the share of physicians recommending branded drugs falls 6.5% relative to physicians whose patient does not face these incentives. With cost-sharing, 1.7% more patients fail to initiate treatment.

Using insights from these preliminary analyses, I test the relative effect of demand and supply-side incentives on both short-run costs and long-run health.

[19]The use of psychotherapy in capitated plans is largely from primary care physicians referring patients to psychiatric specialists; primary care physicians conduct only 9% of all psychotherapy recorded in the sample.

[20]Hellerstein (1998), Jones et al. (2001), and Filippini et al. (2006) demonstrate that prescribing behavior differs according to region, the physician's specialty, and other socioeconomic factors.

[21]During the years available in the data, 14 states mandate that pharmacists dispense the generic form of a prescription written for an off-patent branded compound unless the physician expressly forbids substitution. In the remaining states, pharmacists exercise discretion.

5 Incentives and short-run costs

To test the effect of incentives on treatment choice, I estimate a flexible form for the utility function underlying the observed treatment choices. I choose an estimation approach that allows both observable and unobservable patient and physician heterogeneity to influence the treatment choice. From this empirical model I recover the elasticities of the patients and physician's joint response to incentives. I use the estimates to conduct counterfactual exercises to distinguish among the likely mechanisms through which copayments and capitation influence the cost of physician's treatment recommendation.

5.1 Empirical Model

I estimate the parameters of the joint patient and physician utility function, choosing a specification similar to the theoretical model outlined earlier. The patient cares about an option's effectiveness and his required copayment. In making a recommendation to the patient, the physician accounts for the patient's utility but also maximizes her own private benefits.

I include drug fixed effects, f_j, to proxy for a medication's expected efficacy and tolerability as well as features like the convenience of the required dosing.[22] I measure the patient's sensitivity to copayment levels by including the copayment level in the specification. I allow patients to differ in their sensitivity to price depending on their age, diagnosis, the office visit copayment they face, and whether they have additional chronic medical conditions. I summarize these patient variables in Z_{it}^{Pat}. I also introduce random coefficients on the price variable, labeled α_i, to capture unobserved individual heterogeneity in the patient's price sensitivity. Thus, for individual i on drug j in period t, the patient's utility equals:

$$U_{ijt}^{Pat} = f_j + \alpha_i * copay_{ijt} + \alpha_1^z Z_{it}^{Pat} * copay_{ijt} + \varepsilon_{ijt}^{Pat} \tag{7}$$

where unobservables that vary over time fall into an idiosyncratic error term, ε_{ijt}^{Pat}.

The physician accounts for the patient's preferences but may also react to variables excluded from the patient's utility. Specifically, I allow the physician's utility to depend on the insurer's cost. Finding a negative and significant sensitivity to the insurer's

[22] If firms choose copayment levels based on these product characteristics, including fixed effects in the specification controls for time-invariant unobservables that may drive pricing.

cost indicates that the physician may care about minimizing overall health care costs or may participate in a shared risk arrangement with the insurer. This insurer cost variable varies mostly across plans, but also changes over time, particularly in the period surrounding the introduction of new branded or generic products. I introduce the insurer cost variable with a random coefficient to account for unobserved heterogeneity in responsiveness across the physician population. I also allow the physician to respond differently to the insurer's cost depending on the characteristics of the patient's insurance plan—for example, whether it is a capitated HMO plan—and according to the patient's illness severity. I include these variables in Z_{it}^{Plan}. Finally, I allow physicians to respond differently to copayments depending on the physician's specialty; I include these specialty indicators in Z_{it}^{Phys}:

$$U_{ijt}^{Phys} = \gamma U_{ijt}^{Pat} + \beta_i * (\text{ins. cost}_{ijt}) + \beta^z Z_{it}^{plan} * (\text{ins. cost}_{ijt}) + \alpha_2^z Z_{it}^{Phys} * (\text{copay}_{ijt}) + \varepsilon_{ijt}^{Phys} \tag{8}$$

Substituting the patient's utility in equation (7) into the physician's utility in (8) and rearranging:

$$U_{ijt}^{Phys} = (\gamma\alpha_i + \gamma\alpha_1^z Z_{it}^{Pat} + \alpha_2^z Z_{it}^{Phys}) * \text{copay}_{ijt} + \tag{9}$$

$$(\beta_i + \beta^z Z_{it}^{plan}) * (\text{ins. cost}_{ijt}) + f_j + \varepsilon_{ijt} \tag{10}$$

Here, (α_i, β_i) follow normal distributions, with mean and variance that I estimate. I use a joint error term for the patient and physician, ε_{ijt}, which follows an extreme value distribution. I cannot separately identify γ from α_i and α_1^z. I include it in the above formulation to illustrate that the level of the physician's attention to patient interests may lessen the influence of copayments on the choice. The strength of demand-side incentives relative to supply-side incentives is an empirical question; the elasticities with respect to the policies depend on either the size of γ or the size of α_i and α_1^z relative to β_i and β^z.

To estimate this model, I face one additional hurdle. Even after controlling for drug-specific fixed effects, the insurer's price variable may be correlated with the time-varying unobservable in the model. For example, if there is an advertising campaign in period t, the price might be set in a way that is correlated with the unobserved promotion. The correlation may induce bias in the coefficient on insurer cost in the choice model.[23] To handle this endogeneity concern, I exploit the nature of insurer-

[23]In this setting, the copayments set by the insurer vary less frequently over time than do the

manufacturer negotiations to develop an instrument.[24] If a self-insured firm employs a skilled negotiator or a pharmacy benefits manager to negotiate with drug manufacturers on its behalf, it is likely that insurer-specific year to year price changes reflect the strength of the negotiation. I use the sum of the price changes within an insurer's plan across all drugs except drug j as an instrument for drug j's price. The price changes within the plan help explain the price for drug j at t but should be unrelated to unobserved national advertising for j at period t. I use this instrument in a control function framework, similar to the procedure Petrin and Train (2010) describe. I include the details of this approach in Section 9.2 of the Appendix.

5.2 Results

I estimate three specifications of the empirical model. In the first, I do not control for endogeneity of the insurer cost. The second two specifications follow the control function approach; they differ in the set of patient and physician observables included in the model. I estimate the model using a Bayesian Markov Chain Monte Carlo (MCMC) approach. The MCMC approach offers two benefits. First, it reduces computation. Within the estimation procedure, I collect draws from the conditional distribution of the individual's price sensitivity parameter. I reuse these draws later to predict drug shares under counterfactual pricing policies. Second, in this setting, including individual-specific heterogeneity in treatment choices in the empirical model allows me to fit the data better than a model with fixed coefficients. I choose hierarchical priors to capture flexibly the heterogeneity across consumers.

The top panel of Table 5 contains both the fixed coefficient estimates as well as the estimated parameters of the normally distributed random coefficients on the copayment and the insurer cost.[25] The differences in the estimates in specifications (1) and (2) illustrate the effect of using the instrument to control for the correlation between the insurer's cost and omitted time-varying product attributes. The price coefficient be-

insurer costs, and so there seems less of concern for a correlation of copayments with time varying unobservables.

[24]This design is similar to Grennan (2013), who uses supply-side variation in hospitals' bargaining abilities to instrument for price in medical device demand.

[25]While I consistently estimate these population parameters, I cannot estimate consistently any individual's parameters. I would need to observe multiple choice situations for an individual, say across markets or time, to obtain a consistent estimate of the individual-level parameters (Train (2003)). As a result, in counterfactual predictions, I use Bayes' rule to form a conditional distribution of the individual coefficients, conditioning on the observed first period choice. I draw from this posterior distribution using a Metropolis-Hastings algorithm.

comes more negative with the control function included. The residual from the control function enters the model significantly and with a positive sign.

Specification (2) implies that the baseline sensitivity to patient prices follows a normal distribution with a mean equal to -.535 and a variance of 1.15; the insurer cost parameter has a mean equal to -.612 and a variance of .036. Specification (2) also includes an interaction of the insurer's cost with a capitation indicator. The coefficient on this term suggests capitated doctors care more on average about the insurer's cost than do other physicians. Physicians treating patients diagnosed with more severe illness categories, holding other observables constant, care far less about copayment levels. As in the theoretical model, when the likelihood of relapse or reassessments is high regardless of the treatment selected initially, incentives may have weaker effects on the physician's choice. In addition, I find that psychiatrists place significantly more emphasis on lower copayments in their choice than do general practitioners. Physicians prescribing treatment for sicker patients with more than one serious chronic condition also favor drugs with lower patient out-of-pocket costs.

Specification (3) includes interaction terms of the capitation indicator with drug indicator variables. I use this specification to predict the effect of expanding capitation incentives to cover more physicians. In Figure 2, I illustrate the distribution of patient and physician sensitivities to both copayments and insurer costs using this specification.

To examine model fit, I compare the predicted shares under the mixed logit estimates shown in the "base" column of Table 6 with the raw shares reported in Table 3. The general pattern and magnitudes of the predictions match the observed shares well. I also calculate implied price elasticities in the model, averaged over physician and patient-specific sensitivities. The elasticities from specification (2) vary between -.3 and -.5, depending on the drug treatment. This is within the range of elasticities Goldman et al. (2007) find in their review of the literature on cost-sharing.

5.3 Patient-directed incentives

I use the estimated price sensitivities to illustrate how alternative copayment policies may affect generic drug use and overall health spending. Both the physician and patient's preferences may play a role in generating the observed shares. If physicians shift their prescribing toward cheaper medications under stronger incentives, this may stem from altruism or from pressure applied by the patient. When initiation increases, it may reflect either the physician writing more prescriptions or patients actually filling

the prescription the physician writes.

The results of three counterfactual experiments related to price incentives appear in Table 6. In the first, I change the relative levels of the copayments such that branded drugs cost about $50 per 30 day supply, the 95th percentile of copayments in the data. The result is a meaningful shift toward generics—a 6.6 percentage point increase—with some reorientation in shares toward drugs with lower costs and lower average side effects, such as fluoxetine and citalopram. The outside share increases, however, from 23% to 28%. Examination 2 illustrates the effect of shifting the copayment of generic drugs to zero. In this counterfactual, the outside good share falls slightly while the share of generics increases by about four percentage points. Given the same marginal cost between 'none' and generics, patients and physicians shift to pharmacologic treatment, judging it to have higher expected health returns. Examination 3 shows the effect from changing the underlying insurer cost. The effect is similar to increasing the copayment of the branded treatment.

In interpreting these results, one potential concern is that patients select into particular plans based on the plan's copayment level. Such selection could bias the sensitivity to copayments, if patients with greater health needs purchase plans with lower copayments. I address this concern by exploiting several features of the data. First, I estimate the choice model on data from private insurance claims. In this setting, patients choose from a small range of plans, unlike the larger menu available to patients buying coverage on the individual market or choosing a Medicare Part D plan. As shown in Table 2, the average copayment for branded and generic treatments is fairly similar across both capitated and non-capitated HMO plans, and slightly lower for PPO plans. It does not appear from these summary statistics that the capitation incentive itself correlates strongly with the average level of drug copayments. Second, I restrict the analysis to patients newly diagnosed with depression. Using information on the patient's first treatment upon diagnosis also makes it unlikely that patients have selected into one of their employer's insurance plans based on the expected costs of unforeseen depression treatment. Finally, third, I control for a measure of the patient's health, the Charlson comorbidity index, in the specifications in the top panel of Table 5.[26] I allow the effect of the copayment on treatment choice to differ according to the patient's overall health.

[26]Charlson et al. (1987) define an index that predicts a patient's ten-year mortality as a function of previous diagnoses, including, among others, heart disease, diabetes, HIV/AIDS, and cancer.

5.4 Physician-directed incentives

The predicted shares in Examination 4 in Table 6 reveal the influence of capitation on physician decisions. When insurers pay physicians using capitation, physicians select a distinct distribution of treatments, much like in the raw shares in Table 3. The share of individuals on generics increases from 28% to 38%, a larger increase than the change predicted in the counterfactual in which copayments on generic drugs equal \$0. Under capitation, physicians prefer standard generic drugs including fluoxetine, citalopram, and paroxetine.

There are multiple channels through which capitated payments affect the physician's drug choice. I distinguish between three major hypotheses empirically, each with different welfare implications: (1) capitated physicians seek out drugs that cause fewer patient follow-up visits, since physicians bear the risk of repeat consultations; (2) plans that pay physicians using capitation impose a variety of regulations on the physician that change her behavior apart from the reimbursement scheme; and (3) capitated plans contract with physicians predisposed to cost containment. I look for evidence of each.

To test the first hypothesis, I examine both the initial drug choice and the rate of switching. In the flexible discrete choice model, I find doctors seeing patients on capitation prescribe a distinct set of treatments. Controlling for patient and physician characteristics, capitated physicians favor three generic drug products. I then test whether, all else equal, these treatments are those that engender fewer switches overall. To do so, I conduct a duration analysis. I define a dependent variable that equals the patient's duration on a treatment until the patient switches to a new antidepressant or quits treatment altogether. I allow the hazard of switching to change flexibly over time by employing a piecewise-constant proportional hazard in the empirical specification. I describe the hazard framework in more detail in Section 9.1 of the Appendix.

The hazard model allows me to examine the likelihood of switching away from a drug in a given time interval, for observably similar patients with observably similar insurance plans. I control for a rich set of patient demographics, physician characteristics, and, to capture differing hazards by drug, I include drug ingredient indicator variables, an indicator for whether a drug requires two or more daily doses, and an indicator for whether a drug is branded. I control for the patient's formulary design using the coefficient of variation in the patient's copayments across the drugs in his or her choice set. Finally, I control for the patient's plan type—capitated HMO, non-capitated HMO, or PPO.

I report the estimates in Table 7 and the predicted switching hazard rates by drug in Table 8, where the prediction sets the covariates equal to their distribution in the sample. Comparing the drug preferences of capitated physicians in Table 6 with the hazard predictions in Table 8, I find that those drugs prescribed more often to capitated patients have among of the lowest observed rates of switching, all else equal.

As a second rationalization for the choices of capitated physicians, I test whether coincident incentives employed by capitated HMO plans enter the physician's decision process. In addition to prospective payment, insurers may issue warnings to physicians when they prescribe high volumes of expensive drugs or monitor their actions via electronic medical records. To examine this hypothesis, I collect information at the plan level on the types of incentives employed across capitated HMO plans, non-capitated HMO plans, and PPO plans. In Table 2, I list the frequency of each tool by plan type. For example, the two categories of HMO plans both use formulary incentives more often than PPOs and charge higher prices for "non-preferred" drugs. The capitation effect reported in Table 4 appears when comparing capitated HMOs with non-capitated HMOs. This within-HMO comparison controls for the effects of correlated incentives, suggesting the main findings relate importantly to the reimbursement scheme itself.

Finally, I consider whether the selection of providers into the plan network explains the capitation results. Physicians electing to accept capitated payments for medical services may be those with better knowledge of available drug alternatives or may have a higher sensitivity to patient costs and outcomes. To provide some evidence on this hypothesis, I employ a physician-level dataset, the National Ambulatory Medical Care Survey (NAMCS), which samples patient visits to office-based physicians.[27] The survey collects information on the patient's background and the physician's characteristics, for all patients who visit the surveyed physician in a specific recording interval. The sample provides detailed information on the physician's managed care contracts, the characteristics of her practice and patient population, and on the physician's prescription choices across patients. However, unlike the main dataset, it lacks detail on the payment scheme for any particular patient. That is, when observing the choice for a patient, I cannot identify whether that patient's plan pays the physician using capitation. I therefore analyze variation in the behavior of a cross-section of physicians in the NAMCS data who differ in their capitation share. I collect the NAMCS data for the same sample period and for the same diagnosis classes chosen in the main analy-

[27]National Ambulatory Medical Care Survey, *National Center for Health Statistics*, Hyattsville, MD: 2003-2005.

sis. I then test the hypothesis that physicians who never accept capitation prescribe a distinct distribution of drugs from those that do.

Panel 1 of Table 9 shows the correlations in the survey data across the physician practice characteristics. Panel 2 shows results from a logit model that varies the characteristic, "physician accepts new patients on capitated plans," while holding constant other physician and patient background characteristics. If underlying, stable preferences govern a physician's prescription choices independent of financial incentives, I would expect physicians who accept capitation for some patients to write more generic prescriptions relative to physicians who do not accept capitation.

I present the predictions from this exercise in Panel 2 of Table 9. Physicians who accept capitation for some patients prescribe substantially the same treatments across their entire patient panel as do physicians paid only via fee-for-service schemes. Physicians accepting some capitated patients write slightly fewer branded prescriptions for Lexapro, but the difference in share is not significant nor of the same magnitude as in the main analysis. Overall, the physician-level data provide little evidence that physicians who treat some patients under capitation are predisposed to cost containment.[28]

6 Incentives and health

One contribution of this paper is to add new measurement of the relative effectiveness of supply vs. demand-side incentives in restraining total drug spending. However, these incentives may also affect patient health. I turn now to measuring changes in health due to changes in the strength of incentives. The goal of this measurement is to help inform optimal insurance design, which must balance both short-run costs and long-run health outcomes.

Ideally, one should measure health outcomes using patient-level panel data over long time horizons with detailed medical record information; however, such data are typically not available to researchers. Instead, I develop surrogate endpoints for health outcomes in the depression setting. Specifically, I examine first the rate of adherence to drug care, which Berndt et al. (2002) and other authors in the medical literature link to longer range rates of depression recovery. Second, I examine relapse rates in the period

[28] As a sensitivity, I estimate a choice model that controls for capitation and other physician attributes, such as whether the insurer directly employs the physician. If adding these controls diminishes the effect from capitation, then it may be these attributes—and not the reimbursement scheme alone—that explains observed behavior. As reported in Table 9, the results change very little with these controls.

3-6 months after the patient's first episode of depression. This is an underestimate of the rate of relapse over longer horizons, but may inform the relative influence of supply vs. demand-side incentives on relapse over this short horizon.

I begin with a duration analysis to predict the time at which the patient completely exits depression care as a function of incentives. As in the analysis of the duration to a treatment switch, I specify a piecewise-constant proportional hazard to allow the hazard to vary within a patient episode. The structure also allows me to deal flexibly with censoring in the duration data, which can occur at the last available date in the sample. I again control for a rich set of patient and physician background characteristics, product variables, and variables that capture the plans copayment design and physician payment incentives. Most of the observed exits occur well short of the recommended treatment duration for patients with the depression diagnoses that I select to form the analysis sample. Thus, one should not interpret early exit from care as a positive outcome or an indication of a cure.

I describe the form for the hazard and the likelihood function in detail in the Appendix, Section 9.1. Here, I present the probability that an individual exits care during month m of treatment. The probability that the patient's exit date, t, occurs in month m is:

$$\begin{aligned} P(m-1 \;&\leq\; t < m | t \geq m-1, X_i) = 1 - \alpha_m(X_i, \theta) && (11) \\ &=\; 1 - \exp\left(-\exp(X_i\beta)\lambda_m\right) && (12) \end{aligned}$$

I let the probability that a patient continues treatment beyond period m, $\alpha_m(X_i, \theta)$, be a flexible function of the set of covariates, X_i. Including λ_m in the expression for the probability of continuing allows this probability to be different for each month.

The estimates from the hazard model appear in column (2) in Table 7. The dependent variable reflects the number of monthly decision points that elapse before the observed exit from treatment. Given the form chosen for Equation (12), the sign of each element of the coefficient vector, β, determines how the probability of continuing treatment varies with the patient, product, and insurance plan characteristics. If a covariate has a positive coefficient, raising its value increases the probability that the patient exits treatment relative to the baseline exit rate in that period.

The estimated coefficients on the patient demographics and physician characteristics have the expected signs: male patients and patients with multiple medical conditions exit treatment more rapidly. Relative to the youngest quartile, older patients tend

to remain in treatment longer, though the effect is non-monotonic: patients in the oldest quantile quit more often than do patients in the 50th-75th percentile in age. The adherence rate among patients treated by general practitioners and psychiatrists is statistically indistinguishable for less severe patients but is higher for psychiatrists when the patient suffers from major depression.

Controlling for these demographics, I examine the effect of incentives on adherence. I find the rate of adherence for patients on PPO plans and capitated HMO plans is similar, though slightly lower for capitated patients. The non-capitated HMO plans have far worse adherence. I illustrate these differences using predicted exit probabilities in Table 10, conditioning on the drug chosen initially. All else equal, a major depression patient seeing a general practitioner under capitation has a rate of exit between 9% and 30% after the initial month of treatment. The rate is roughly equivalent for PPO patients but is higher by an average of nearly eight percentage points for non-capitated HMO patients. This finding suggests that while stronger cost controls within HMOs may discourage patients from seeking care and remaining in care, the addition of capitation in such plans actually pushes treatment durations higher. There is, however, room for improvement. The American Psychiatric Association's guideline for depression treatment recommends patients diagnosed with depression follow a treatment course for at least 6 months (Karasu et al. (2000)). The data make clear that the existing incentive structure fails to encourage the recommended treatment regimen, particularly for individuals diagnosed with major depression.

The rate of adherence are similar to results in Pomerantz et al. (2004), Melfi et al. (1998) and Akincigil et al. (2007). Poor adherence is a problem in that it is associated with worse long-run outcomes. For example, results from Berndt et al. (2002) suggest that, compared to patients who take second generation antidepressants for more than 1 month, those patients who quit within one month have an eight percentage point lower probability of full remission and a 15 percentage point lower probability of partial remission within four months of diagnosis.

Next, I quantify the health effects through an additional measure available in the panel data, the rate of relapse. I define a relapse as a new office visit or prescription filled after a gap of 3 months from the last observed office visit or from the exhaustion of the patient's final prescription, whichever is later. For example, if a patient exhausted the supply of his last prescription on January 1, 2004, I examine the next six months of data. If the patient did not receive care for depression in January, February, and March, but did appear for depression care sometime after April 1, I consider the office

visit a relapse. To simplify the problem of censoring, I look only for new depression care occurring between 3 and 6 months after the initial active treatment period ended. Overall, 33,657 unique individuals had episodes with a 3 month gap after the last treatment, followed by at least 3 more months of data to allow me to identify whether the patient relapsed during that period.

The results of this logit analysis appear in Table 11. I condition on the length of time the individual received treatment in the initial period before quitting, to ensure that the estimates do not simply reflect differences in the initial treatment intensity or quality. The results thus compare, for a given initial treatment length, the rate of return for care in the ensuing 3 months. In this subsample, 5.4% of patients suffered a relapse.[29] Stronger incentives worsen the rate of relapse, as illustrated in panel 2 of Table 11. Holding constant the length of the initial treatment episode and a rich set of patient background characteristics, both higher copayments and the introduction of capitation lead to statistically significant increases in the rate of relapse in outpatient and prescription care. The relapse rate increases from to 5.4% to 6.0% with all patients on capitated plans; doubling copayments leads to a 0.4 percentage point increase in relapse. Over two years, assuming a constant rate of relapse, 35.9% of patients will relapse in the baseline case without incentives. Given the logit estimates, 38.0% of patients facing a doubling of copayments and over 39% facing capitation incentives will likely suffer a relapse. The rate of relapse under cost-sharing would be higher if copayments increased at a greater rate.

This rate of relapse likely represents a lower bound on the true rate. In the logit analysis, I neglect relapse into inpatient care. In addition, my panel is relatively short. Examining relapse at dates beyond six months would produce a cleaner measurement, as the difficulty of scheduling a follow-up visit may artificially decrease the number of visits observed even after a three month window.

7 Optimal insurance design

I combine the results from both the static choice model and the duration and relapse analyses to inform the policymaker's incentive design problem. First, I use the product

[29] Karasu et al. (2000) find that 50% of patients relapse over two years. This is equivalent to a constant rate of relapse of 2.9% per month over 24 months. Over three months, the literature would predict that 8.3% of patients relapse. The rate in my sample is slightly lower because I do not measure relapses that occur when a patient seeks inpatient care.

choice model to predict how alternative incentives affect the initial choice of the physician. I convert these choice predictions into a dollar cost to the insurer, to quantify one portion of the design tradeoff the insurer faces. Second, I summarize the health consequences to stronger incentives to capture the remaining element of the insurer's design problem.

Looking only at prescription drug costs, I sum the individual-specific insurer costs by patient, subtracting off the copayments these patients pay for their treatment.[30] With existing incentives, insurers' average costs equal $35 per patient for the first 30 days of drug treatment. Increasing the branded copayment up to the 95th percentile reduces the insurers' drug costs 41% to $21 per patient, as insurers take in more revenue from copayments, physicians prescribe cheaper generics, and 5% more patients fail to fill even one prescription.[31] More modest increases in branded copayments lead to smaller cost savings for the insurer. A policy that decreases generic copayments to $0 actually raises drug costs slightly by 7% to $38 per patient per month. The composition of use shifts toward generics, but more patients initiate treatment and the revenue from copayments drops. Finally, paying all physicians by capitation decreases drug costs by 16%. Thus, capitation appears to have a stronger effect on short-run drug costs than changes to the relative copayments. However, these savings neglect the costs from relapse and from the increase in referrals to specialists' care for psychotherapy, which may be substantial.

I quantify the effect of incentives on health by analyzing both adherence and the rate of relapse under stronger incentives. The duration analysis suggests that stronger incentives on the demand-side lead to poorer adherence, which translates into lower rates of recovery and higher rates of relapse. On the supply side, adherence declines with HMO incentives, but the addition of capitation incentives largely reverses this fall; capitated plans had rates of adherence much closer to PPO plans than to non-capitated HMO plans. The analysis of the relapse measure, though limited due to the short horizon of 3-6 months available in the panel data, supports the predicted decline in health under greater cost-sharing and, to a lesser extent, under supply-side incentives.

Together, the measurement of the changes to costs and health suggests the optimal

[30]The negotiated payment between the insurer and pharmacy typically accounts for the copayment revenue collected by the pharmacy. See Levy (1999).

[31]Patients may also leave an insurer's plan in response to high cost-sharing. The feedback of incentives on the insurer's overall enrollment can also hurt profitability. I lack data on patient plan enrollment changes, and so neglect this dimension of the insurer's maximization in my analysis.

insurance design may vary by disease. For conditions like depression that may become chronic, the insurer can minimize long-run costs by employing weaker incentives, similar to PPOs, with relatively weak demand-side cost sharing. In particular, when the rate of adherence drives long-run outcomes, capitation incentives appear to outperform cost-sharing in reducing costs without substantially increasing the rate at which patients leave treatment. For acute conditions with little risk of relapse, stronger demand-side incentives, possibly in combination with capitation, may minimize costs.

8 Conclusion

The interrelationships between patients, physicians, and insurers grew out of two characteristics of the market for prescription drugs: patients lack the knowledge to select their own treatment and also face uncertainty in their future health status. The theoretical model predicts that when physicians possess more information than their patients, the physician's treatment selection may diverge from the patient's preference. Absent first best contracts, insurers operating in this market can encourage physicians to prescribe cost-effective drugs by employing supply and demand-side incentives.

In the data, the application of these incentives involves trade-offs. Conditional on recommending drug treatment, both capitation and copayment policies encourage the selection of cheaper alternatives within the choice set, shifting prescribing from popular branded drugs to a common, effective generic. Higher copayments on the demand-side, however, can cause price-sensitive patients to quit the recommended treatment course prematurely. Capitation, by placing the risk of follow-ups on the physician, encourages physicians to concentrate prescribing on drugs with simpler dosing and moderate effectiveness for a broad population.

The relative benefits of using demand and supply side incentives depends on disease characteristics, including the likelihood of costly relapse. If follow-up costs are low, strong supply-side policies along with cost-sharing provide a sharp reduction in short-run costs. If the illness may become chronic, minimizing long-run costs requires weaker demand-side incentives and weaker HMO supply-side regulation to encourage greater adherence.

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9 Appendix

9.1 Duration Analysis

I conduct duration analyses on both the time until a patient switches treatment and the time until the patient quits treatment. I follow closely the methodology summarized in Wooldridge (2010). I choose a flexible specification of the hazard function to permit the hazard to: (1) vary within a patient's episode, (2) vary according to observable patient, physician, and insurance plan characteristics, and (3) handle censoring at the end of the panel data. For the description below, I write the durations in terms of exiting treatment. The same empirical form applies when the dependent variable instead represents the duration before a treatment switch.

The probability that an individual exits care at a date within the first period of treatment is:

$$P(0 \leq t < 1 | t \geq 0, X_i) = 1 - \alpha_1(X_i, \theta) \tag{13}$$

where $\alpha_1(X_i, \theta)$ is probability that a patient continues in treatment beyond period 1. The general form for probability of continuing at period m equals:

$$\alpha_m(X, \theta) = \exp\left(-\int_{a_{m-1}}^{a_m} h(s; X_i, \theta) ds\right) \tag{14}$$

For $h(t; X_i, \theta)$, I choose a piecewise-constant proportional hazard:

$$h(t; X_i, \theta) = \exp(X_i \beta) * \lambda_t \tag{15}$$

The hazard depends on a set of individual-specific covariates, X_i. Here, λ_t represents a time-period specific level of the hazard. With this hazard, I rewrite the probability that the patient continues treatment after period m:

$$\alpha_m(X, \theta) = \exp\left(-\int_{a_{m-1}}^{a_m} \exp(X_i \beta) \lambda_m ds\right) \tag{16}$$

$$= \exp\left(-\exp(X_i \beta) \lambda_m (a_m - a_{m-1})\right) \tag{17}$$

I choose months as the time period given the periodic nature of my observed data. Here, $a_m = m$, meaning a_m equals a count of the number of months. Thus, for every month, $a_m - a_{m-1} = 1$.

I build a likelihood function from the probability of exiting care in a given month. For patient i, the likelihood of exiting treatment in month m equals:

$$\left[\prod_{h=1}^{m-1} \alpha_h(X_i, \theta)\right] [1 - \alpha_m(X_i, \theta)] \tag{18}$$

Here, the first term in brackets reflects the probability that the patient remains in treatment in months one through $m-1$. The second term equals the probability that the patient exited care in month m. I alter this form slightly, as in Wooldridge (2010), to account for possible censoring in the panel data for those patients whose treatment episodes extend to the final month of my sample. Letting $cens_i = 1$ if the panel is censored for i, the log likelihood for individual i is:

$$\left[\sum_{h=1}^{m_i-1} \log(\alpha_h(X_i, \theta))\right] + (1 - cens_i) * (1 - \alpha_m(X_i, \theta)) \tag{19}$$

To calculate the log likelihood for the entire sample, I sum Equation (19) over all individuals in the sample, $i = 1, ..., N$.

9.2 Control Function within Mixed Logit

I describe below the algorithm I use to control for the potential endogeneity of price, here the insurer's cost. The framework follows closely the procedure and notation in Petrin and Train (2010).

The utility for individual i under choice j is:

$$U_{ij} = V(p_{ij}, X_{ij}, \beta_i) + \varepsilon_{ij}$$

Here, X_{ij} are the exogenous variables for individual i and product j. The concern is that price, p_{ij}, may be correlated with the unobserved term, ε_{ij}. The control function approach requires the researcher to find a set of instruments, Z_{ij}, that are correlated with the endogenous price but uncorrelated with the error term in the choice model. More precisely:

$$p_{ij} = W(Z_{ij}, \gamma) + \tau_{ij}$$

where ε_{ij} and τ_{ij} are independent of Z_{ij} but τ_{ij} and ε_{ij} are correlated. I decompose ε_{ij}

into an expectation conditional on τ_{ij} and deviations from this mean:

$$\varepsilon_{ij} = E(\varepsilon_{ij}|\tau_{ij}) + \widetilde{\varepsilon}_{ij}$$

The deviations, $\widetilde{\varepsilon_{ij}}$, are not correlated with τ_{ij} by construction.

The conditional expectation serves as the control function. I can add the control function as an extra explanatory variable in my choice model such that the remaining error term will not be correlated with the endogenous price:

$$U_{ij} = V(p_{ij}, X_{ij}, \beta_i) + CF(\tau_{ij}, \lambda) + \widetilde{\varepsilon}_{ij}$$

I specify the control function and the conditional expectation of $\widetilde{\varepsilon}_{ij}$ following Example 2 in Petrin and Train (2010). I separate the error in the choice model into an extreme value and a joint normal component. Let the utility function, price equation, and control function take the following forms:

$$\begin{aligned} U_{ij} &= V(p_{ij}, X_{ij}, \beta_i) + \varepsilon^1_{ij} + \varepsilon^2_{ij} \\ p_{ij} &= W(Z_{ij}, \gamma) + \tau_{ij} \\ CF(\tau_{ij}, \lambda) &= \lambda\tau_{ij} \end{aligned}$$

where ε^1_{ij} and τ_{ij} are jointly normal. Here, ε^2_{ij} is independently and identically distributed and follows an extreme value distribution. The conditional distribution of ε^1_{ij} is normal with mean $\lambda\tau_{ij}$ and a constant variance. Adding the control function as an additional regressor in the model gives:

$$U_{ij} = V(p_{ij}, X_{ij}, \beta_i) + \lambda\tau_{ij} + \widetilde{\varepsilon}^1_{ij} + \varepsilon^2_{ij}$$

where $\widetilde{\varepsilon}^1_{ij}$ follows a normal distribution with zero mean and constant variance.

I estimate this model in two stages. In a first stage, I recover τ_{ij} by running a least squares regression of the insurer's cost on the set of instruments Z_{ij}, which include the exogenous covariates in the choice model and the leave-one-out plan-specific price changes. I save the residual from this regression, τ_{ij}. In a second stage, I estimate the choice model as a mixed logit, adding the residual, τ_{ij}, from the first stage as an additional regressor with a normally distributed random coefficient. Here, τ_{ij} is centered at λ with variance equal to the constant variance of $\widetilde{\varepsilon}^1_{ij}$.

10 Figures and Tables

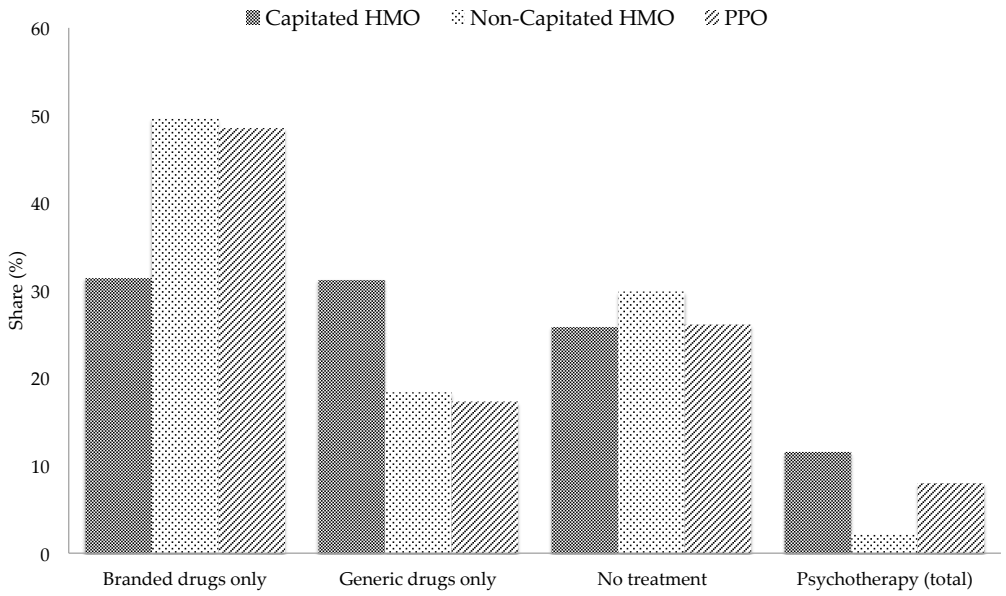

Figure 1: Treatment choice, by plan type

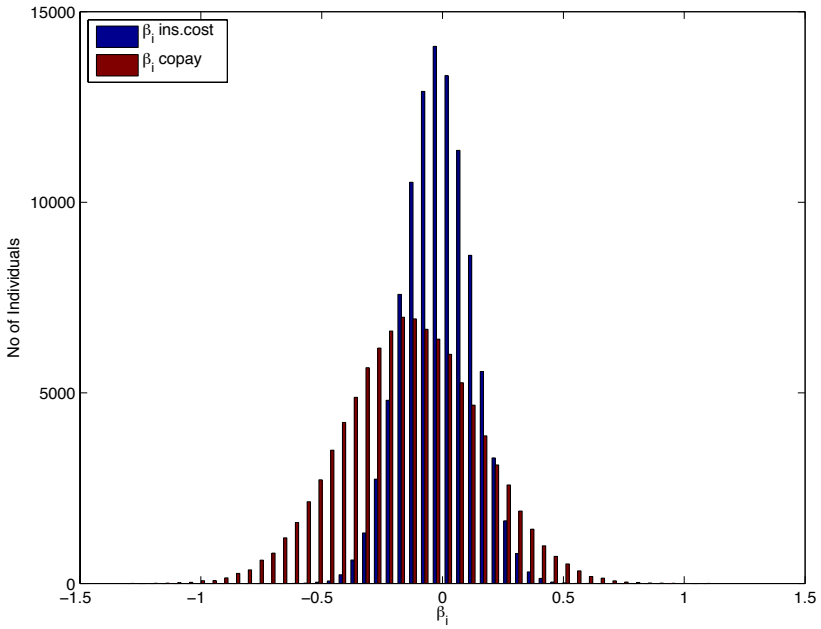

Figure 2: Distribution of Mixed Logit Random Coefficients. For insurer cost and patient cost per day supply.

Table 1: Summary Statistics on Product and Patient Characteristics

Panel 1: Prices for one month's supply and shares, by product

				Insurer Cost ($/month supply)			Copayment ($/month supply)			Market Share		
Ingredient Name	Product Name	Subclass	Brand?	2003	2004	2005	2003	2004	2005	2003	2004	2005
None	None	None	-	-	-	-	-	-	-	29.5	28.5	23.5
Psychotherapy only	Psychotherapy only	None	-	-	-	-	-	-	-	0.1	0.6	6.3
Citalopram HBr	Celexa	SSRI	Yes	72.9	76.9	80.2	19.3	25.6	35.9	4.6	3.0	0.1
Citalopram HBr	Citalopram HBr	SSRI	No	-	52.9	27.6	-	8.8	10.0	-	0.2	4.4
Escitalopram Oxalate	Lexapro	SSRI	Yes	63.4	64.5	68.5	19.9	21.5	27.7	15.1	12.8	12.8
Fluoxetine HCl	Fluoxetine HCl	SSRI	No	30.2	27.2	25.4	8.0	8.3	9.3	7.7	12.0	11.0
Fluoxetine HCl	Prozac	SSRI	Yes	133.2	163.6	193.1	24.5	35.5	43.4	0.4	0.7	0.2
Paroxetine HCl	Paroxetine HCl	SSRI	No	68.3	60.3	44.0	9.6	9.8	10.7	1.8	4.5	4.8
Paroxetine HCl	Paxil CR	SSRI	Yes	81.7	84.2	86.9	19.5	21.4	26.1	4.9	3.4	1.5
Sertraline HCl	Zoloft	SSRI	Yes	79.8	83.9	87.7	18.2	21.9	29.3	13.1	10.4	10.2
Duloxetine HCl	Cymbalta	SNRI	Yes	-	105.3	114.8	-	28.4	34.5	-	0.5	2.6
Venlafaxine HCl	Effexor	SNRI	Yes	73.8	80.1	84.1	17.8	21.1	25.2	0.5	0.6	0.5
Venlafaxine HCl	Effexor-XR	SNRI	Yes	109.4	119.0	122.4	18.6	22.1	28.6	9.1	8.0	7.4
Bupropion HCl	Bupropion HCl	NDRI	No	36.9	68.0	68.7	7.6	10.0	12.2	0.3	3.6	4.7
Bupropion HCl	Wellbutrin XL	NDRI	Yes	102.7	104.6	112.9	20.5	21.8	29.4	1.6	4.6	5.7
Amitriptyline HCl	Amitriptyline HCl	TCA	No	5.5	5.5	5.1	5.8	5.9	6.3	0.9	0.9	0.8
Mirtazapine	Mirtazapine	NaSSA	No	63.2	44.7	38.0	8.9	8.5	9.5	0.7	0.8	0.7
Trazodone HCl	Trazodone HCl	SM	No	8.1	8.2	7.6	6.2	6.5	7.1	1.8	2.3	2.0
									Total observations by year:	12,369	44,141	41,602

Panel 2: Table of individual-level covariates in product choice model

					Quantiles				
Variable	Mean	Std Dev	Min	Max	5%	25%	50%	75%	95%
Office Visit Copay	10.3	11.3	0.0	252.4	0.0	0.0	10.0	15.0	30.0
Patient Age	42.1	12.4	18.0	64.0	20.0	33.0	43.0	52.0	61.0
Avg. County Income (000s)	42.6	11.0	18.7	86.4	28.5	35.1	41.2	46.6	63.9
1{Diagnosis, Major Depression}	27.5%								
1{Female}	71.1%								
1{General Practitioner }	44.0%								
1{Psychiatrist}	28.1%								
Total # of Observations:	98,112								

Notes:
1. Source: Thomson Reuters' MarketScan Outpatient and Drug Claims Databases, years 2003-2005. Sample subset to individuals diagnosed with one of four classes of depression: major depression, dysthymia, depressive reactions, and depression not otherwise specified. The sample excludes pregnant women, individuals with concurrent diagnoses of bipolar disorder or schizophrenia.
2. Copayments reflect the patient's out-of-pocket cost for a 30-day supply of medication. The insurer cost is the reported cost responsibility of the patient's insurer for a 30-day supply. This price excludes rebates commonly offered to insurers by drug manufacturers. The mean is taken across available plans in the data.
3. The drug subclasses reported differ according to the ingredient's effect on the concentration of neurotransmitter chemicals in the brain. SSRIs selectively inhibit the reuptake of serotonin; SNRIs inhibit the reuptake of serotonin and norepinephrine; NDRIs affect norepinephrine and dopamine; TCAs, tricyclic antidepressants, unselectively block the reuptake of serotonin; SMs modulate serotonin; and NaSSAs act by antagonizing various adrenergic and serotonin receptors.

Table 2: Observed supply and demand-side incentives across benefit plans, by broad plan type

	Plan Type			Differences across Types			
				Cap. - Non-cap. HMO		Capitated HMO -PPO	
Plan Incentives	Capitated HMO	Non-Capitated HMO	PPO/Comprehensive	Change	P-value	Change	P-value
Incentives for generic drugs (lower coinsurance/copayments)	92.7%	86.2%	86.3%	6.5%	0.20	6.4%	0.08
Use of formulary tiers for drug copayments	53.7%	62.1%	55.1%	-8.4%	0.24	-1.5%	0.43
Psychiatric services carved out	41.5%	41.4%	20.2%	0.1%	0.50	21.3%	0.00
Patient cost for psychiatric outpatient services increases with # of visits	12.2%	24.1%	12.9%	-11.9%	0.10	-0.7%	0.45
Precertification requirements for inpatient care	43.9%	82.8%	61.6%	-38.9%	0.00	-17.7%	0.02
Utilization review for inpatient care	17.1%	27.6%	34.6%	-10.5%	0.15	-17.5%	0.00
Case management for inpatient care	19.5%	31.0%	55.5%	-11.5%	0.14	-36.0%	0.00
Prescription copay, generic ($/month supply)	8.47	8.16	7.18	0.31	0.36	1.29	0.03
Prescription copay, brand name ($/month supply)	17.68	18.77	13.95	-1.10	0.24	3.73	0.02
Prescription copay, non-formulary brand ($/month supply)	31.67	36.06	21.45	-4.40	0.12	10.21	0.00
Annual maximum for outpatient psychiatric visits (# of visits)	38.44	37.31	39.87	1.14	0.40	-1.43	0.31
Number of plans observed of each type:	41	29	263				

Notes:
1. Source: Thomson Reuters' MarketScan Benefit Plan Design Database, years 2003-2005.
2. Patients in either category of Health Maintenance Organization (HMO) must choose from a particular list of providers for all non-emergency care. Each patient chooses a Primary Care Physician to manage his care, with specialist care by referral only. Capitated plans, unlike the non-capitated versions, pay for all physician services prospectively by enrollee.
3. Remaining variables in multinomial logit set to: Age quantile: 40th-60th; Gender: Female; Plan type: Capitated HMO; Copayment Incentives: Yes; Coinsurance Incentives: No; In MSA?=Yes; Region=West; Office visit copayment=$10.

Table 3: Drug Treatment Shares, by Patient and Physician Characteristics

Product	Brand Name?	Subclass	Overall	Capitated HMO	Non-Capitated HMO	Patient covered by PPO	Treated by General Practitioner	Treated by Psychiatrist	Diagnosis of Major Depression
None	-	None	27.74	27.47	30.29	27.38	26.56	27.01	24.55
Psychotherapy only	-	None	1.67	2.39	0.33	1.53	0.19	5.07	2.79
Lexapro	Yes	SSRI	13.11	8.47	15.73	15.63	16.26	9.25	12.12
fluoxetine HCL	No	SSRI	11.05	17.55	7.35	7.47	8.72	12.56	11.43
Zoloft	Yes	SSRI	10.70	8.15	12.05	11.96	12.50	8.67	10.00
Effexor-XR	Yes	SNRI	7.88	6.19	8.56	8.91	9.12	6.85	8.34
Wellbutrin XL	Yes	NDRI	4.69	3.51	3.27	6.08	5.14	4.61	5.61
Paroxetine HCL	No	SSRI	4.30	5.83	3.16	3.60	4.16	4.17	4.00
Bupropion HCL	No	NDRI	3.68	5.58	3.30	2.56	3.03	4.90	4.07
Citalopram HBr	No	SSRI	1.98	2.74	1.22	1.79	1.93	2.21	2.07
Celexa	Yes	SSRI	1.96	1.83	2.79	1.61	1.69	2.36	2.16
Total # of individuals in subpopulation			98,139	34,760	13,227	42,637	43,186	27,569	26,947

Notes:
1. Source: Thomson Reuters' MarketScan Outpatient and Drug Claims Databases, years 2003-2005. Selected products shown.
2. Patients in either category of Health Maintenance Organization (HMO) must choose from a particular list of providers for all non-emergency care. Each patient chooses a primary care physician to manage his care, with specialist care by referral only. Capitated plans, unlike the non-capitated versions, pay for general practitioner services prospectively by enrollee. Preferred Provider Organizations (PPOs) do not require a primary care physician or referrals, and reimburse physicians retrospectively.
3. Major depression (ICD-9 codes 296.2, 296.3) is one of four depression categories composing the analysis dataset.
4. The option 'None' reports the share of individuals diagnosed with depression in an outpatient office visit who never fill a prescription for an antidepressant. This can occur when the physician does not prescribe drug treatment or when the patient fails to fill a prescription. If the patient had no observed drug claims but did receive psychotherapy treatment, his experience would contribute to the option labeled "Psychotherapy only". Individuals receiving both psychotherapy and a drug treatment would appear in the share of the specific drug treatment dispensed.

Table 4: Multinomial Logit Examination of Drug Category Choice

	Treatment Type			
Predicted Probabilities (in %)	Branded drug only	Generic drug only	Psycho-therapy	No treatment
Panel 1: Plan Type/Physician Payment Regime				
Prob. HMO, capitated	37.67	43.05	1.06	18.22
Prob. HMO, non-capitated (POS)	49.28	29.48	0.22	21.02
Prob. PPO/Comprehensive	50.57	29.27	1.41	18.75
HMO, cap. - HMO, non-cap.	(11.62)	13.58	0.85	(2.80)
Std. error of change	0.71	0.72	0.06	0.51
HMO, cap. - PPO/Comp.	(12.91)	13.79	(0.35)	(0.53)
Std. error of change	0.56	0.58	0.05	0.38
Panel 2: Cost Sharing Regimes				
Prob. w/Copay Incent, No Coin Incent	50.57	29.27	1.41	18.75
Prob. w/No Copay Incent, No Coin Incent	57.10	25.24	0.60	17.06
Copay Incent- No Copay Incent, No Coin	(6.52)	4.03	0.81	1.69
Std. error of change	0.75	0.72	0.07	0.49

Notes:
1. Source: Thomson Reuters' MarketScan Outpatient and Drug Claims Database, years 2003-2005.
2. Exercise sets remaining background variables to the following values: Specialty=General Practitioner; Diagnosis=major depression; Gender=Female; Region=West; Age Quintile=40th-60th; In MSA?=Yes; Restrictive Annual Cap on Psych. Visits=No; Psychiatric Carve-Out=No; Mandatory Gen. Subs State?=No; Office Visit Copayment = $10; County Average Income = Median.
3. The psychotherapy category includes patient episodes in which the physician prescribed both drug treatment and psychotherapy.

Table 5: Mixed Logit Estimates

	(1)		(2)		(3)	
Variable	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error
insurer cost	-0.114	0.015	-0.612	0.008	-0.017	0.031
patient drug copay	-1.668	0.072	-0.535	0.071	-0.131	0.024
variance, insurer cost	0.199	0.010	0.036	0.004	0.019	0.002
variance, patient drug copay	2.835	0.239	1.148	0.141	0.078	0.009
Age*copay	0.002	0.001	0.002	0.001	-0.293	0.034
Office visit copay*copay	0.010	0.001	0.005	0.001	-	-
1{MDD} *copay	0.652	0.026	0.544	0.011	-	-
1{Psychiatrist} *copay	-0.734	0.022	-0.568	0.015	-	-
1{Cap. HMO}*insurer cost	-0.185	0.008	-0.137	0.007	-	-
1{Non-Cap. HMO}*insurer cost	-0.009	0.012	0.012	0.011	-	-
1{high charlson index}*copay	-0.234	0.020	-0.832	0.019	-0.293	0.034
1{high charlson index}*insurer cost	-0.036	0.009	0.204	0.010	0.042	0.012
residual for insurer cost	-	-	0.817	0.012	0.249	0.028
variance, error component for insurer cost	-	-	0.040	0.004	0.021	0.003
Drug effects included?	Yes		Yes		Yes	
Interactions of drug effects with capitation?	No		No		Yes	
With control function?	No		Yes		Yes	

Distribution of coefficients in the population:

Calculated using 100,000 draws from a normal distribution with the estimated parameters from specification (3)

Random Coefficient	Mean	Std Dev.	% of draws with coefficient below zero
insurer cost	-0.0174	0.1379	55.1%
patient drug copay	-0.1325	0.2785	68.2%

Notes:

1. Source: Thomson Reuters' MarketScan Outpatient and Drug Claims Databases, years 2003-2005.

2. Mixed logit estimated via Markov Chain Monte Carlo methods. The estimates come from a sequence of 20,000 draws collected after a burn-in sequence of 75,000 draws to ensure convergence to the relevant posterior distributions.

3. Price variables have random coefficients. I report above both the mean estimates and the variance estimates. The variances come from the main diagonal of the covariance matrix calculated using draws from the posterior distribution.

Table 6: Mixed Logit - Predicted Drug Choice Probabilities for Selected Antidepressants

			Predicted Shares									
			Base		(1)		(2)		(3)		(4)	
			Original sample		Copay of branded drugs = 95th pctile ($50 for 30 days)		Copay of generic drugs set to $0		Insurer costs for branded drugs increase by 20%		All patients enrolled in capitated HMO plans	
Product Name	Class	Brand?	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
No drug treatment	None	N	22.71	0.16	27.68	0.27	21.08	0.27	25.96	0.19	27.75	0.29
Celexa	SSRI	Y	1.55	0.03	1.25	0.04	1.48	0.05	1.39	0.03	1.68	0.11
Citalopram HBr	SSRI	N	2.53	0.03	3.13	0.02	2.89	0.03	2.88	0.03	3.18	0.05
Lexapro	SSRI	Y	14.14	0.05	11.13	0.06	13.50	0.05	13.08	0.04	9.29	0.06
Fluoxetine HCL	SSRI	N	12.36	0.12	15.29	0.17	13.95	0.12	14.04	0.11	19.20	0.17
Paroxetine HCL	SSRI	N	5.38	0.01	6.62	0.01	6.19	0.01	6.13	0.01	6.48	0.04
Paxil CR	SSRI	Y	3.12	0.01	2.20	0.01	2.97	0.01	2.68	0.01	2.02	0.02
Zoloft	SSRI	Y	11.79	0.08	9.30	0.05	11.27	0.07	10.26	0.07	8.75	0.08
Cymbalta	SNRI	Y	1.59	0.03	1.33	0.03	1.52	0.03	1.29	0.03	0.89	0.07
Effexor-XR	SNRI	Y	8.89	0.02	6.43	0.02	8.49	0.02	6.85	0.02	5.95	0.04
Bupropion HCL	NDRI	N	4.48	0.02	5.49	0.02	5.24	0.02	5.13	0.02	5.66	0.04
Wellbutrin XL	NDRI	Y	5.58	0.06	4.05	0.07	5.32	0.08	4.44	0.07	3.33	0.12
Amitriptyline HCL	TCA	N	0.74	0.16	0.92	0.27	0.79	0.27	0.84	0.19	0.67	0.29
Trazodone HCL	SM	N	1.52	0.11	1.88	0.13	1.65	0.10	1.72	0.10	1.90	0.18
Overall Generic Share			28.19		34.77		32.04		32.08		38.14	
Overall Branded Share			49.10		37.54		46.88		41.96		34.11	

Notes:
1. Source: Thomson Reuters' MarketScan Outpatient and Drug Claims Databases, years 2003-2005.
2. Predicted shares in the baseline column and columns (1)-(3) rely on coefficients from specification (2) reported in Table 5. Predicted shares in column (4) rely on coefficients from specification (3) in Table 5.
3. Standard errors computed using draws from the posterior distribution, conditioning on the observed first period choice. The computation involves further simulation to account for the sampling distribution of the estimated coefficients themselves.

Table 7: Estimates from Piecewise-Constant Proportional Hazard on Treatment Duration

	(1) Y=1{Patient switches treatment or exits in period t}			(2) Y=1{Patient exits treatment in period t}		
Variable	Coeff	Std Error	T-stat	Coeff	Std Error	T-stat
1{patient diagnosed with MDD}	-0.168	0.235	0.714	0.174	0.276	0.630
1{patient is male}	0.013	0.031	0.416	0.065	0.039	1.673
1{age in [25,50) percentile}	-0.086	0.043	1.987	-0.119	0.043	2.774
1{age in [50,75) percentile}	-0.135	0.040	3.348	-0.201	0.056	3.565
1{age in [75,1) percentile}	-0.129	0.052	2.502	-0.170	0.052	3.297
1{no Charlson comobidities}	-0.086	0.040	2.177	-0.076	0.040	1.899
1{visits a psychiatrist}	0.020	0.070	0.291	0.030	0.081	0.370
1{visits a non-psychiatric specialist}	0.006	0.033	0.188	0.029	0.035	0.834
1{Visits a psychiatrist and diagnosed with MDD}	-0.094	0.079	1.194	-0.204	0.103	1.979
1{patient covered by a non-capitated HMO}	-0.430	0.097	4.428	-0.531	0.098	5.397
1{patient covered by a capitated HMO}	-1.101	0.102	10.749	-1.478	0.129	11.496
Coefficient of variation in copayments of a patient's plan	-0.859	0.076	11.363	-0.989	0.064	15.503
Coefficient of variation*1{plan is a non-capitated HMO}	1.149	0.147	7.819	1.336	0.158	8.437
Coefficient of variation*1{plan is a capitated HMO}	1.742	0.132	13.219	2.191	0.154	14.184
1{dosing frequency >1-2x per day}	0.555	0.088	6.341	0.473	0.091	5.187
1{prescribed branded drug}	0.448	0.056	7.936	0.456	0.071	6.410
time period 1	1.155	0.179	6.464	0.543	0.058	9.390
time period 2	0.837	0.122	6.870	0.482	0.050	9.568
time period 3	0.675	0.102	6.614	0.397	0.045	8.782
time period 4	0.688	0.115	5.965	0.443	0.052	8.429
time period 5	0.612	0.108	5.680	0.360	0.038	9.543
time period 6	0.573	0.107	5.346	0.377	0.050	7.548
time period 7	0.486	0.092	5.300	0.302	0.044	6.899
time period 8	0.540	0.099	5.439	0.302	0.050	6.028
time period 9	0.427	0.091	4.672	0.329	0.059	5.575
time period 10	0.650	0.145	4.494	0.378	0.073	5.183
time period 11	0.718	0.188	3.817	0.509	0.119	4.273
Includes drug ingredient indicators?		Yes			Yes	
Includes interaction of diagnosis with drug indicators?		Yes			Yes	

Notes:
1. Sample includes all panel data observations on the prescription history of the 98,112 unique patients collected from Thomson Reuters' MarketScan databases for years 2003-2005.
2. The excluded categories include: 1{any diagnosis other than MDD},1{ age in [0,25) percentile}, 1{At least one Charlson comorbidity}, 1{patient visits a general practitioner}, 1{patient covered by a PPO plan}, and 1{patient begins on drug in the TCA class}.

Table 8: Predicted hazard rates of switching treatment. Estimates from column (1) in Table 7.

	Time Period					
Product	1	2	3	4	5	6
Amitriptyline HCL	0.459	0.361	0.304	0.309	0.280	0.265
Bupropion HCL	0.383	0.296	0.247	0.251	0.227	0.214
Wellbutrin XL	0.352	0.271	0.225	0.229	0.206	0.195
Citalopram HBr	0.218	0.163	0.134	0.137	0.123	0.115
Celexa	0.318	0.243	0.201	0.205	0.185	0.174
Cymbalta	0.209	0.157	0.129	0.131	0.118	0.111
Lexapro	0.318	0.243	0.201	0.205	0.185	0.174
Fluoxetine HCL	0.310	0.236	0.196	0.199	0.179	0.169
Prozac	0.439	0.343	0.288	0.293	0.265	0.251
Mirtazapine	0.398	0.309	0.259	0.263	0.238	0.225
Nefazodone	0.557	0.448	0.381	0.387	0.353	0.335
Nortriptyline HCL	0.459	0.361	0.304	0.309	0.280	0.265
Paroxetine HCL	0.294	0.223	0.185	0.188	0.169	0.159
Paxil	0.419	0.326	0.273	0.277	0.251	0.237
Zoloft	0.325	0.248	0.206	0.209	0.189	0.178
Trazodone HCL	0.557	0.448	0.381	0.387	0.353	0.335
Effexor	0.419	0.326	0.273	0.278	0.251	0.237
Effexor-XR	0.269	0.203	0.168	0.171	0.154	0.144

Notes:
1. Sample includes all panel data observations on the prescription history of the 98,112 unique patients collected from Thomson Reuters' MarketScan databases for years 2003-2005.
2. Predictions based on the observed patient and physician characteristics in the analysis dataset. The predicted probabilities use the estimates from the switching hazard estimation reported in block (1) in the hazard estimates table.

Table 9: Examination of Physician Characteristics on Prescribing Behavior

Panel 1: Correlations in Physician Practice Characteristics, reported with p-values

Variable	Physician's Patient Rev. Share from Managed Care <=50%	Physician an Employee	Physician's Patient Rev. Share from Private Ins. <=50%	Physician Specialty = General Practitioner	Physician Specialty = Psychiatrist	Physician Accepts New Patients on Capitated Plans
Physician's Patient Rev. Share from Managed Care <=50%	1.000	-0.103	0.373	-0.012	-0.032	0.013
		<.0001	<.0001	0.611	0.167	0.5829
Physician an Employee		1.000	0.075	0.115	-0.159	0.124
			0.001	<.0001	<.0001	<.0001
Physician's Patient Rev. Share from Private Ins. <=50%			1.000	-0.067	0.027	0.077
				0.004	0.246	0.001
Physician Specialty = General Practitioner				1.000	-0.837	0.130
					<.0001	<.0001
Physician Specialty = Psychiatrist					1.000	-0.140
						<.0001
Physician Accepts New Patients on Capitated Plans						1.000
Mean	60.57%	24.65%	47.15%	49.24%	41.92%	63.36%
Number of observations	1,809	1,809	1,809	1,809	1,809	1,809

Panel 2: Prediction Exercises, Multinomial Logit on Drug Compound Choice

	Observed Data		With Background Controls		With Background and Incentive Controls	
Drug Compound	Physician Accepts Cap. Plans (%)	Physician Does Not Accept Cap. Plans (%)	Accepts Cap. - Doesn't Accept (%)	Standard Error of Difference	Accepts Cap. - Doesn't Accept (%)	Standard Error of Difference
None	14.1	13.6	0.9	1.5	1.3	1.6
Citalopram HBr (Celexa)	4.9	6.3	(1.5)	1.1	(0.8)	0.6
Escitalopram Oxalate (Lexapro)	14.8	15.8	(2.9)	2.3	(3.6)	2.7
Fluoxetine HCL (Prozac)	9.9	10.7	(1.4)	1.2	(0.9)	0.9
Paroxetine HCL (Paxil)	7.2	9.0	0.1	2.1	0.5	2.2
Sertraline HCL (Zoloft)	13.3	13.6	0.2	1.7	0.3	1.6
Venlafaxine HCL (Effexor, XR)	13.6	10.5	2.4	2.1	1.3	2.2
Bupropion HCL (Wellbutrin, XL/SR)	15.4	14.4	1.8	1.2	1.7	1.3
Trazodone HCL (Serzone)	6.7	6.1	0.4	0.4	0.3	0.4

Notes:
1. Source: National Ambulatory Medical Care Survey, years 2003-2005.
2. Pearson correlation coefficients reported in Panel 1. P-value reported for null hypothesis that coefficient = 0.
3. Background controls in multinomial logit: Gender = Female; Race = White; Age Quantile = [.4,.6]; Patient pay type = private insurance; Specialty = General Practitioner.
4. Incentive controls in multinomial logit: Physician revenue from managed care <50%?=Yes; Physician an employee?=No; Physician revenue from private insurance<50%=Yes.

Table 10: Predicted hazard rates of exit from treatment as a function of patient and physician characteristics. Estimates from column (2) in Table 7.

	(1) Physician Specialty		(2) Plan type (for general practitioner)			(3) Coefficient of variation in copayments	
Product	Psychiatrist	General practitioner	Capitated HMO plan	PPO plan	Non-capitated HMO plan	Low coefficient of variation	High coefficient of variation
Amitriptyline HCL	0.206	0.240	0.240	0.238	0.327	0.199	0.296
Bupropion HCL	0.170	0.199	0.199	0.197	0.274	0.165	0.247
Wellbutrin XL	0.168	0.196	0.196	0.194	0.270	0.162	0.244
Citalopram HBr	0.104	0.122	0.122	0.121	0.172	0.100	0.154
Celexa	0.159	0.186	0.186	0.184	0.257	0.153	0.231
Cymbalta	0.077	0.091	0.091	0.090	0.128	0.074	0.115
Lexapro	0.159	0.186	0.186	0.184	0.257	0.153	0.231
Fluoxetine HCL	0.179	0.209	0.209	0.207	0.287	0.173	0.259
Prozac	0.267	0.309	0.309	0.307	0.414	0.259	0.377
Mirtazapine	0.185	0.216	0.216	0.214	0.296	0.179	0.267
Nefazodone	0.163	0.191	0.191	0.189	0.263	0.158	0.237
Nortriptyline HCL	0.206	0.240	0.240	0.238	0.327	0.199	0.296
Paroxetine HCL	0.153	0.180	0.180	0.178	0.248	0.148	0.224
Paxil	0.231	0.268	0.268	0.266	0.363	0.223	0.329
Zoloft	0.183	0.213	0.213	0.211	0.292	0.176	0.264
Trazodone HCL	0.163	0.191	0.191	0.189	0.263	0.158	0.237
Effexor	0.221	0.257	0.257	0.254	0.348	0.213	0.316
Effexor-XR	0.144	0.169	0.169	0.167	0.234	0.139	0.211

Notes:
1. For the above exams, I set the independent variables equal to the following values in the hazard prediction: patient suffers from major depression, is female, is in the age quartile of 25-50%, has no Charlson comorbidities, and has coefficient of variation in the copayments equal to the median in the data (.6795).
2. Predictions are for plan exit between initiation and the end of the first month of treatment.
3. "Low" coefficient of variation equals the 25th percentile value in the data (.5034); High coefficient of variation equals the 75th percentile in the data (.8840).

Table 11: Rates of Illness Relapse Conditional on Incentives and Demographics

Panel 1: Logit Estimates

Variable	Estimate	Std. Error	T-stat	Average Derivative
Background Characteristics*				
Intercept	-2.299	0.223	10.3	-0.116
Total time treated in 1st episode	-0.004	0.000	14.4	0.000
1{Psychiatrist}	0.310	0.074	4.2	0.016
1{Other specialist}	-0.235	0.065	3.6	-0.012
Drug Characteristics				
1{NDRI}	0.382	0.131	2.9	0.019
1{TCA}	-0.160	0.214	0.7	-0.008
1{SNRI}	-0.037	0.169	0.2	-0.002
1{NaSSA}	-0.164	0.266	0.6	-0.008
1{SM}	0.100	0.214	0.5	0.005
1{Branded}	-0.190	0.083	2.3	-0.010
1{Reformulation}	-0.124	0.112	1.1	-0.006
1{Frequency of Dosing 2+ /day}	-0.205	0.158	1.3	-0.010
Percentage of study participants w/ nausea	0.391	0.928	0.4	0.020
Plan Incentives				
Drug copay/day supply	0.123	0.058	2.1	0.006
1{Capitated HMO}	0.132	0.074	1.8	0.007
1{Non-capitated HMO}	-0.156	0.076	2.1	-0.008
Office visit copayment	0.001	0.002	0.7	0.000
1{Carve out used}	-0.419	0.058	7.2	-0.021
	Number of observations in estimation:			33,657

*Includes demographic controls: age quantiles interacted with gender, 1{patient lives in MSA}, patient home region (North East, North Central, South, West), patient diagnosis (by reported ICD-9 code), average income in patient's home county.

Panel 2: Prediction Exercises

Case	Prob. of relapse[2]	Case - Baseline	Std. Error of Change
Observed covariates	5.42%	-	-
All patients treated under capitated HMO plans	5.98%	0.56%	0.24%
All patients begin drug treatment on an SSRI	5.19%	-0.23%	0.15%
Drug copayments increase 100% from baseline	5.82%	0.40%	0.20%
All plans involve mental health carve-outs	4.18%	-1.24%	0.16%

Notes:
1. Source: Thomson Reuters' MarketScan Outpatient and Drug Claims Databases, years 2003-2005.
2. Relapse = 1 if patient returned to a physician for depression care between three and six months after an initial treatment episode.
3. Omitted Categories in estimation: Diagnosis is "depression not otherwise specified"; Specialty is General Practitioner; Plan is PPO; Initial drug in SSRI class; Gender/age quintile is 1{Female}*1{Age quintile = [0.4,0.6)}; Region is West.