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HOW DOES COST-SHARING AFFECT DRUG PURCHASES? INSURANCE REGIMES IN THE PRIVATE MARKET FOR PRESCRIPTION DRUGS

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This research is a substantial revision and extension of our earlier 2004 NBER working paper no. 10738 "Does Cost Sharing Affect Compliance? The Case of Prescription Drugs".

How Does Cost-Sharing Affect Drug Purchases? Insurance Regimes in the Private Market for Prescription Drugs

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ABSTRACT

Insurance for prescription drugs is characterized by two types of cost-sharing: flat copayments and variable coinsurance. We develop a theoretical model to show that refill purchases of preventive drugs (compliance) are lower under coinsurance due to the consumer's exposure to variation in drug prices. Coinsurance creates countervailing incentives. Consumers who never comply under flat copayments might find it optimal to comply if they drew a relatively low price under coinsurance. In contrast, consumers who always comply under flat copayments might stop complying if they drew a relatively high price under coinsurance. Our theory shows the second effect dominates under certain distributional assumptions about health states. Empirically, we derive comparable models for compliance behavior in the two regimes. Using claims data from eight large firms, we focus our analysis on diabetes, a common chronic condition that leads to severe complications when not continuously treated with medications. Propensity score methods are used to create matched samples for the two insurance regimes. We find that when coinsurance and flat copayments have the same expected out-of-pocket of $9, at least 34% of patients under copayments would fully comply and refill their medication over the next 90 days, compared to only 24% under coinsurance. Similarly, under copayments, moving from the 25th percentile to the 75th percentile of cost sharing results in a significantly lower shift into the non-compliance state compared with coinsurance. Thus, the empirical results confirm the main theoretical predictions. This research is a substantial revision and extension of our earlier 2004 NBER working paper no. 10738.

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1 Introduction

Overall drug spending in the private sector grew approximately 15-20 percent per year during the 1990s (Thomas et al, 2002), and the Centers for Medicare and Medicaid Services project similar rates of growth through the next decade. In 2002, national expenditures on prescription drugs amounted to over $160 billion, with employer-sponsored insurance covering most of the bill (Woellert, 2002). Moreover, between 2006 and 2008 the federal government's share of the national spending on drugs was predicted to increase from 22% to 40% due to the introduction of the Medicare Part D prescription drug benefit for the elderly (Frank, 2004). This benefit is expected to increase drug spending by 12% to 17% (Yang et al, 2004).

Driven by concerns over rising costs, Medicare, employers, and insurers are now designing pharmaceutical benefit plans to allow greater consumer cost sharing. Early evaluations of such plans suggest that increased cost sharing is indeed helping to bring about lower consumer spending on prescription drugs, and hence, lower employer costs. For example, Joyce et al (2002) have shown that a doubling of copayments decreased total spending on drugs from 19% to 33%. However, Huskamp et al (2003) find little change in spending for some drugs classes aimed at chronic conditions (statins, ACE inhibitors, and proton-pump inhibitors) after copayment increases. Goldman et al (2004) show that this is due to the fact that chronically ill patients decrease utilization of their nonessential medications more so than their chronic care drugs when copayments are increased.[1]

In most circumstances, economists would conclude that such developments are rational responses to market imperfections in the presence of insurance — increased patient cost sharing reduces moral hazard and excessive medical consumption, thereby improving social welfare (Pauly, 1974). Indeed, empirical research (spurred by the Rand Health Insurance Experiment) has shown that reasonable increases in copayments lead to reduced medical

[1]Similar patterns occur with copayments for outpatient services. Liang et al (2004), show that the use of copayments discourage the use of controversial services, such as prostate cancer screening, but have no effect on recommended services like mammography screening for breast cancer.

expenditures in a variety of situations, with little adverse impact on health (Manning et al, 1987; Newhouse 1993).

However, the case of prescription drugs is more complex. Often drugs are associated with preventive efforts to reduce further illness and complications, and the patient might not share the doctor's clinical understanding of these long run benefits of drugs. In this case underutilization may be the problem, and 'too much' cost sharing may lead to a loss of welfare. This was theoretically shown to be possible for preventive drugs, such as statins, by Ma and Riordan (*JEMS*, 2002), and, generally, for preventive care by Dor (2004). In fact, empirically, Hsu et al (2006) found that a $1,000 cap on drug benefits resulted in lower drug use and poorer control of blood pressure, lipid levels, and glucose levels among Medicare+Choice beneficiaries.

Moreover, underuse of drugs with respect to clinical guidelines has long been a problem even before the additional concerns of increased cost-sharing arose. In a study of three of the ten largest health plans in California in 1999, underuse of drugs was severe: only 27.5% of antidepressant users received the recommended 6 months of continuous therapy, only 48% of asthma patients received at least one inhaled corticosteroid drug, and only 54.5% of patient with congestive heart failure received an ACE inhibitor (Gilberg et al 2003). Similar underuse of beta blockers after a heart attack are well documented nationally (National Healthcare Quality Report, 2003). In half the states, 45% of patients with an irregular heart beat did not receive follow-up blood thinning drugs (Warfarin) to prevent a stroke (Leatherman and McCarthy, 2002).

In this paper, we will explore the degree to which cost-sharing can act as a barrier to preventive effort as measured by 'compliance'—the adherence to refilling of prescriptions of preventive care drugs without interruption. In particular, we will focus on the impact of cost-sharing on compliance with anti-diabetic medications. It should be noted that we are not merely interested in levels of copayments. Rather, we distinguish between two main insurance regimes, namely fixed copayments and variable coinsurance (i.e., percentage copayments). While economists have begun to explore the issue of the impact of cost-

sharing on utilization (so called *demand management*)[2], this important distinction in cost-sharing structures has not been previously considered. While Ma and Riordan (2002) have developed the demand management theory for the trade-off between premiums and the level of copayments, in this paper we develop the demand management theory for the trade-off between coinsurance and copayments. This trade-off seems to be the most cogent trade-off currently underway in the health insurance marketplace. In fact, since drug prices increase each year, many employers have been moving from flat and tiered copayments to a coinsurance rate (Hewitt Associates, 2002). Even the preventive care-focused HMO, Kaiser Permanente, has switched to coinsurance for specialty drugs in 2008 due to their rapid price increases. This forces the patient to pay 30% of any cost increase, if the coinsurance rate is 30% for example, otherwise, under a flat copayment the employer will have to pay 100% of the cost increase. However, critics argue that coinsurance is more difficult for patients since it leads to greater variation and uncertainty in out-of-pocket expenses, causing greater non-compliance (Bymark and Waite, 2001).

Indeed, as we argue below, the incentives facing consumers under these two regimes are not identical, and therefore responses to cost-sharing should not be identical. To motivate this, we develop a simple theory; our empirical results conform with the theoretical prediction that compliance will be lower under variable coinsurance than under flat copayments. This is due to the fact that the patient does indeed face greater uncertainty in out-of-pocket drug costs under coinsurance.

Why Diabetes?

Diabetes is one of the most common chronic condition for which prescription medications exist, with 18 million Americans, or 6.2 percent of the U.S. population estimated to have

[2]The issues explored in these studies are quite different than ours. For instance, Crown et al, (2003), focus on the role of physicians in asthma prescription behavior, while Ridley (2004) focuses on the role of promotional drug advertisements on demand. They find conflicting results with regard to the impact of copayments on utilization. Ellison et al (1997) consider full price effects rather than copayments, and find some evidence of positive cross-price elasticities for drug substitutions within the same therapeutic class.

this diagnosis. It is the leading cause of adult blindness, kidney failure, and non-trauma amputations, and a leading cause of heart disease. 180,000 people die each year from diabetes in the U.S., making it the sixth leading cause of death. The prevalence of diabetes in the U.S. increased by more than 30% over the last ten years. Moreover, the annual costs of diabetes in medical expenditures and lost productivity climbed from $98 billion in 1997 to $132 billion in 2002. As the incidence of diabetes reaches epidemic proportion, leading to spiraling costs, the need to undertake prevention measures is becoming even more pronounced.

There are two major forms of the disease. Type I diabetes occurs in about 10 percent of cases; in this manifestation of the disease, a person is unable to produce insulin, the major hormone in the body that regulates blood sugar level. Persons with type I diabetes are dependent on daily insulin injections, but few oral prescription medications are available. In type II diabetes mellitus, persons either produce low levels of insulin or the insulin produced is deficient in regulating blood sugars. For this variant of the disease, five types of oral prescription medications are available: Sulfonylureas (SU), Non-SU (Meglitinides), Metformin, Thiazolidinediones (TZD), and alpha-Glucosidase Inhibitors (AGI). Each of these drugs targets a separate organ site in the body to control blood sugar levels, as illustrated in Table 1. These five pharmacological methods of controlling of blood sugar can substantially delay or prevent the costly medical complications arising from diabetes (see Cohen et al, 2003, for instance).

Compliance with these medications is of recent importance, since it was found that only 55% of diabetics keep their blood sugar under control (*National Healthcare Disparities Report*, 2008). A person is considered compliant if he or she adheres to the anti-diabetic drug regimen prescribed by a physician (Hughes et al, 2001; Dezii, 2000). Since these anti-diabetic medications are intended to be taken permanently, measurement of compliance is relatively straightforward when tracking such individuals. In this paper, we will examine patient compliance with all five anti-diabetic drugs in Table 1. In particular, we focus on compliance in terms of purchasing prescription refills to cover the 90 days after using all

the pills supplied in the initial prescription. Our main concern is that increases in patient cost-sharing levels for these drugs may induce some patients to not comply with their anti-diabetic medications[3]. Indeed, we find that increases in cost-sharing from the 25th percentile to 75 percentile in copayments (from $6 to $11) increased the number of diabetics who never complied within 90 days by 9%. For diabetics facing a coinsurance rate rather than a flat copayment, an increase from the 25th percentile to 75 percentile in coinsurance (from 23% to 42%) increased the number of diabetics who never complied within 90 days by 25%.

The paper is organized as follows. First, section 2 sets up a theoretical model of the patient's decision to comply. Section 3 describes the data. Section 4 delineates the empirical methods. Section 5 discusses the empirical results and simulations. Section 6 concludes with a discussion.

2 Theory Model

Cost-sharing for prescription drugs by the patient-consumer can occur either in the form of a fixed copayment (e.g., $25 per prescription) or in the form of a coinsurance rate (e.g., 20% of the final retail price of the prescription). This distinction between fixed copayments and variable payments under coinsurance creates fundamentally different constraints for patients. With a fixed copayment, the patient knows exactly what she will pay out-of-pocket for her next prescription, namely, a flat dollar amount. Under coinsurance, the patient is exposed to any fluctuations in retail drug prices. Below, we present a simple theoretical model that reflects the different sets of incentives that consumers face in each of the two cost-sharing regimes.

Suppose a patient currently has a prescription for a chronic condition. The patient must decide whether to refill the prescription once it runs out. Let y be the patient's income. As in the demand theories of Ma and Riordan (2002) and Glazer and McGuire (2002), we

[3]In fact, Karter et al, (2003), show that use of outpatient diabetic services decline with copayment increases.

assume that there is a continuum of consumers, where each patient has a unique level of sickness s distributed on $[0, 1]$ with cumulative distribution $G(s)$ and density $g(s)$. This variation in s captures the variation in how well diabetics cope without their medications. Healthy patients ($s = 0$) able to exercise regularly may have less severe symptoms, while patients with the poorest health ($s = 1$), with, say, very unstable glucose levels, may require hospitalization shortly after stopping their medications. That is, if the patient does not refill her medication, she will experience a loss in health $L(s)$, and her reservation utility of not complying will be $U(y - L(s))$, where $L'(s) > 0$ and where U is an increasing, concave or linear utility function.

Next, suppose that the random retail price p of the next prescription (30-day supply) is generated by a cumulative distribution $F(p)$ with mean price $E(p) = \bar{p}$ and variation σ^2 on domain $[p_L\ ,\ p_H]$. We assume the patient can learn the retail price before deciding to refill the medicine. Define $C(p)$ to be the out-of-pocket payment that the patient must pay for the drug:

$$C(p) = \begin{cases} c & \text{under copayments} \\ rp & \text{under coinsurance,} \end{cases} \tag{1}$$

where c is the flat copayment and r is the coinsurance rate. Let V be the gross value that the patient places on the drug for which she is debating whether to refill, so that the net value of the drug is $V - L(s)$.[4] Next, let $e(s) = es$ be the patient's effort or personal disutility required to refill the medication, with $e > 0$. Note that sicker patients will necessarily have to exert greater effort in order to refill their medications. This is corroborated in our data where we find that sicker patients are much less likely to comply.[5] Thus, the patient's net benefit of taking the medication is $V - es - L(s)$. Then, the patient's utility when taking a medication is $U(y + V - es - L(s) - C(p))$. Thus, the patient will comply and refill her medication only if her utility is higher under medications than without medications: $U(y+V-es-L(s)-C(p)) > U(y-L(s))$. Since U is increasing and weakly concave, this

[4] A more general model where V is allowed to vary with s is considered in Appendix 2.

[5] This can be seen in Figure 1 and in the regressions of Table 3, where compliance is negatively related to the presence of "four or more chronic conditions" under both coinsurance and flat copayments.

holds if the following inequality holds:

$$y + V - es - L(s) - C(p) > y - L(s). \tag{2}$$

The left-hand side of (2) captures the net economic value of the next prescription, and the right-hand side captures the utility of not getting the next prescription. Note that (2) reduces to

$$V - es - C(p) > 0. \tag{3}$$

That is, the patient will refill the medication if the value of refilling exceeds the out-of-pocket cost of the drug and the effort of refilling. From (3), we can define the patient indifferent between complying and not complying at cost $C(p)$ as

$$s^* = \frac{V - C(p)}{e}. \tag{4}$$

Then from (3) and (4), patient s will comply with her medication only if $s < s^*$.[6] Then, $G(s^*)$ is the proportion of the population who will comply. More specifically, if we assume that, on average, the out-of-pocket is the same for both copayments and coinsurance ($c = rE(p)$), the probability of compliance over the entire population under copayment $C(p) = c$ is

$$Pr(comply|copayment) = G(s^*) = G\left(\frac{V - c}{e}\right) = G\left(\frac{V - rE(p)}{e}\right). \tag{5}$$

However, for the patient s facing coinsurance out-of-pocket $C(p) = rp$, the refill compliance inequality (3) will hold only for patient s with $s < \frac{V - rp}{e}$. So, the expected probability of compliance over the entire population under coinsurance is

$$Pr(comply|coinsurance) = EG\left(\frac{V - rp}{e}\right), \tag{6}$$

where the expectation E is over prices.[7]

[6]This accords with our empirical data in Figure 1, where compliance declines with s, as measured by the medical possession ratio (the percentage of days in the year that the patient possesses a medication).

[7]Note that equations (5) and (6) are generally not equal since $G(\frac{V - rE(p)}{e}) \neq EG(\frac{V - rp}{e})$ when G is nonlinear.

Comparing coinsurance in (6) with flat copayments in (5), we see that there is a trade-off. The disadvantage of coinsurance is that a person may draw a higher price than average and comply less than they would have under flat copayments. The advantage of coinsurance is that a person may instead draw a lower price than average and comply more than under flat copayments. Thus, it is not immediately clear whether more people are expected to comply under flat copayments than under coinsurance. As we show next, whether the flat copayment regime induces more compliance than the coinsurance regime depends on the distribution $G(s)$ of the sick. The magnitude of the difference in compliance between regimes depends on the variance of the drug price, σ^2.[8]

Proposition 1 *Suppose that the expected out-of-pocket under coinsurance is equal to the flat copayment* ($rE(p) = c$). *Then, the probability of medication compliance over the entire population under coinsurance is*

$$Pr(comply|coinsurance) \simeq Pr(comply|copayment) + \frac{r^2\sigma^2}{2e^2}G''(s^*). \tag{7}$$

Thus,

(1) coinsurance induces less compliance than flat copayments when the population's marginal distribution of illness is declining at the indifferent patient ($G''(s^*) < 0$).

(2) coinsurance induces more compliance than flat copayments when the population's marginal distribution of illness is increasing at the indifferent patient ($G''(s^*) > 0$).

[8]In our previous work we used the mean-variance utility function to model the effect of price uncertainty on compliance decisions (Dor and Encinosa, 2004). That model was somewhat restrictive in that it did not incorporate the dependence of patients behavioral responses on health states. By using more general utility functions we now show that neither insurance regime dominates the patient's medication purchase decision unambiguously. Rather, the dominance of copay versus coinsurance is determined by the distribution of health states in the population. For instance, price increases under coinsurance are more of an impediment to compliance when patients are sufficiently healthy to benefit from standard medication therapies. Thus, which effect may initially dominate becomes an empirically testable issue, which we address by providing the distribution of health states in our data.

Proof: See Appendix 1. A proof for the more general case where value V is a function of severity s is provided in Appendix 2.

Proposition 1 leads to two basic results:

• First, from (7) we see that the magnitude of the difference in compliance between flat copayments and coinsurance increases with the variance of price, σ^2, and with the coinsurance rate, r. Copayments and coinsurance induce the same level of compliance if there is no variation in drug prices ($\sigma^2 = 0$). However, it turns out that there is substantial variation in prescription drug prices, both longitudinally and cross sectionally, with drug prices exhibiting a high level of price dispersion even within the same geographical market.[9]

• Second, from (7) we see that whether coinsurance induces more compliance than flat copayments depends on the marginal distribution of illness (G'') at the indifferent patient s^*. In fact, in Figure 1, we see that $G''(s) < 0$ at every s in our data.

The intuition behind Proposition 1 is simple. Note that the patient s^* is indifferent between complying and not complying under flat copayment c (from (4)). Coinsurance will have two effects, one on each two groups of people: those patients above s^* and those below s^*:

(1) Note that the people with $s > s^*$ never comply under flat copayment c. Thus, if they were exposed instead to coinsurance r and random out-of-pocket rp (with mean $E(rp) = c$), they might just start complying if they drew a really low price p. That is, coinsurance might induce more compliance under coinsurance than under flat copayments for patients $s > s^*$.

[9] In our own data we find that drug prices do vary on a monthly basis. While overall prices increased 8% over the 18 months, prices moved in both directions. For example, Glucotrol decreased by 27% while Glyset increased by 17%. Similarly, in our own data there was a high degree of price dispersion within the same insurance plan. While the coefficient of variation (standard deviation/mean) for price for the overall sample was 0.50, within-plan coefficients of variation ranged from 0.24 to 1.32.

(2) Note that the people with $s < s^*$ always comply under flat copayment c. Thus, if they were exposed instead to coinsurance r and random out-of-pocket rp (with mean $E(rp) = c$), they might just *stop* complying if they drew a really high price p. That is, coinsurance might induce less compliance under coinsurance than under flat copayments for patients $s < s^*$.

So which of these two effects dominates? Clearly, the second effect will dominate if the density $g(s)$ of illness places more weight on the patients with $s < s^*$ than on the group of patients with $s > s^*$. This occurs if $g(s)$ is declining at s^* (i.e., $g'(s^*) < 0$). This is exactly what Proposition 1 says. Recalling that $G'(s) = g(s)$, Proposition 1 says that coinsurance will induce less compliance than flat copayments when the marginal distribution of illness is declining at the indifferent patient, $G''(s^*) < 0$, or $g'(s^*) < 0$.

Thus, whether coinsurance induces more compliance than flat copayments depends on the marginal distribution of illness at the indifferent patient. In general, most common distributions are usually single-peaked in the middle of the density. In that case, they start out convex ($g' = G'' > 0$) and then become concave after the peak ($g' = G'' < 0$). In practice, most copayments appear to be set so that, on average, more than the median of patients comply under flat copayments (we find 70% of all patients comply). This suggests that the threshold point s^* of non-compliance is often well to the right of the median and the peak of the population density and well into the final concave portion of the density ($G'' < 0$). So, the most common outcome in Proposition 1 is for coinsurance to induce less compliance than copayments (i.e., $G''(s^*) < 0$ in (7)). We will verify this to be the case empirically for the preventive case of diabetic medications, where, in Figure 1, we see that $G''(s) < 0$ at every s in our data.

Finally, the different behavior between coinsurance and flat copayments predicted by Proposition 1 leads to a phenomenon that would not be observed by standard demand theory. First, suppose that the flat copayment c did not change. Then standard demand theory would not detect a change in compliance. However, while c does not change, for a

coinsurance out-of-pocket rp with a constant expected out-of-pocket $r\bar{p} = c$, we may have r and $\bar{p}$ varying while c remains constant. These fluctuations in r and $\bar{p}$ while c remains constant are not innocuous. An increase in r would expose consumers to a greater risk of drawing a higher or lower price than expected, which would affect compliance as we saw above in Proposition 1. The increase in r would be accompanied with a commensurate decrease in $\bar{p}$ so that $r\bar{p} = c$. This decrease in price would encourage more compliance. Thus, the overall net effect on compliance from changes in r and p could be positive or negative. Unfortunately, standard demand theory would detect no change since the average out-of-pocket c did not change. Thus, in this paper we go beyond standard demand theory and present a specification that can detect such nuanced changes in compliance within the coinsurance regime.

To empirically capture this nuance, we specify an empirical model based on the theoretical specifications from Proposition 1. We are mainly interested in how p and r should enter the empirical model, e.g., multiplicatively or separately. Equation (7) provides direct guidance for variable specification in the empirical model. In general, (7) gives us the following empirical specification for the cost-sharing variables.

$$Prob\{comply = 1\} = \begin{cases} \beta c & \text{under copayments} \\ \beta r\bar{p} + \gamma r^2 & \text{under coinsurance.} \end{cases} \tag{8}$$

The coefficient $\beta < 0$ captures the *standard demand theory effect of the out-of-pocket* on compliance. The coefficient γ will capture any additional *coinsurance effect* even when on average $rp = c$ while r and p still vary. Note that $\gamma < 0$ if $G''(s^*) < 0$ in (7).

3 Data

In this analysis we use one of the largest available databases of privately insured individuals in the U.S., which is the MarketScan database maintained by the Medstat group. This database encompasses up to 3.5 million individuals who are covered by employer-sponsored health insurance offered by about forty large firms. These include both regular

employees and annuitants (retirees). The complete database contains various files with detailed information on medical conditions, insurance coverage, and payments for persons with any insurance claims for inpatient, outpatient, and prescription drug services. For purposes of this study five different files belonging to MarketScan 1999-2000 and the MarketScan Medicare Supplement were linked to create a single analysis file. The first file was the MarketScan Drug Benefit File, which contains the insurance drug claims for all individuals who purchased prescription drugs. The second was the Employer Benefit Plan Design (EBPD) database, with information on benefit design and drug copayment structure from some of the larger employers in MarketScan, offering a total of 50+ insurance plans with prescription drug benefits. The third was the MarketScan Enrollment File, which linked individuals to their health plan enrollment history. The fourth and fifth files, respectively, were the MarketScan Hospital Inpatient File and the Outpatient Services File containing information on patients' medical conditions and certain demographic characteristics. Finally, the 1999 and 2000 Redbooks (Medical Economics Company, 2001) were used to obtain additional explanations about the particular prescription drugs for diabetes as they appear in the data.

We focus on adults over the age of eighteen with chronic type II diabetes who require oral anti-diabetic medications on an ongoing basis as previously described (Table 1). We use any ICD-9 Type 2 diabetes diagnosis on any inpatient or outpatient claim over a two year period to identify Type 2 diabetics. Access to detailed patient information allows us to track patient compliance, as measured by the sequence of prescription refills within a defined time interval. We observe a 19 month period from June 1, 1999, to December 31, 2000, and consider individuals who are continuously enrolled with drug coverage over this entire period. To allow for a uniform 90 day tracking interval for all observations, we only track individuals with at least one purchase of an anti-diabetic drug prescription with a 30-35 day drug supply that started between June 1, 1999 and September 1, 2000, and that ended no later than October 1.[10] This resulted in an initial sample of 54,649 persons.

[10]About 80% of the prescriptions were 30-35 days. The remainder of the prescription were 60-90 days. To allow for a uniform tracking period these were excluded from our sample. Note that mail orders, which

Merging the EBPD resulted in a sample of 28,031 individuals belonging to eight large firms for which we had drug copayment information. Of these, 20,464 individuals belonged to 14 insurance drug benefit plans that required consumers to pay a flat copayments per prescription, while 6,567 individuals belonged to three drug benefit plans that used coinsurance rates (See Table 2).[11] These two subsamples constitute the "Raw Sample," with its descriptive statistics given in Table 3.

Within the Raw Sample, for some control variables, like "out-of-pocket," it can be seen that the coinsurance subsample has different characteristics than the copayment subsample. Thus, we also construct the "Matched Sample" for the copayment sample in Table 3, consisting of a subset of copayment patients with similar characteristics as the coinsurance patients. By using the version 3.0.0 pscore2 propensity score matching routine of Leuven and Sianesi (2003), we match 6,537 patients from the 20,464 copayment sample patients to 6,537 coinsurance sample patients. To do this, we first create the propensity score with a logit regression of the probability that the patient has coinsurance (as opposed to a flat copayment), controlling for the 18 covariates in the copayment regression of Table 3. Next, using the nearest-neighbor method (Dehejia and Wahba, 2002; Becker and Ichino, 2002), we create the matches by balancing propensity scores across the 18 covariates. Thirty coinsurance sample observations lacked a common region of support and were excluded (Becker and Ichino, 2002). As can be seen in Table 3, the Matched copayment patients and the coinsurance patients now have very similar characteristics for most of the covariates. The median absolute value of the bias in the covariates between copayment and coinsurance patients was reduced from 41.9 to 8.6 due to the matching.[12] Patients from all eight firms appear in the matched sample.

Next, the 18 covariates and financial variables are described in detail. First, as in

employ the longer prescription cycles, have become more common since the end of our study period, growing from 9% nationally in 2000 to 13% in 2005 (Stagnitti 2008).

[11] A fuller discussion of the benefit features in these data is available in Encinosa (2002).

[12] The bias is the difference in the sample means between copayment and coinsurance patients as a percentage of the square root of the average of the sample variances in the copayment and coinsurance patients. See Rosenbaum and Rubin (1985).

Goldman et al (2004), the prices are weighted prices. The weighted prices are constructed for the drug benefit plans in the following manner. First, note that by focusing on diabetes, we are able to exploit a clinical trait, major metabolic defect (Table 1), to assign individuals to three classes of drugs that are medically indicated independently of insurance status. For each metabolic defect we were able to create a weighted price using the share of persons using a particular drug within that group. In particular, there are three drug classes, based on which organs in the human body the drug targets to control metabolism. The first drug class consists of Sulfonylureas and Meglitinides, which target pancreatic beta cells (Table 1) to address defection insulin secretion. The second class addresses insulin resistance and consists of Biguanides (Metformin) and Thiazolidinediones (TZD) which target the skeletal muscles, liver, and adipose tissues. The third class consists of the Alpha-Glucosidase Inhibitors (AGI), which target the small intestines to increase carbohydrate absorption. Thus, overall, the out-of-pocket payment and transacted price per prescription are averaged over 17 plans, 3 drug classes, and 3 time periods consisting of the three six-month intervals between June 1, 1999, and December 31, 2000. The averages are taken on a total of 213,635 prescriptions. Out of the 153 potential cells for the sample (17 plans x 3 drug classes x 3 periods), we observe 75 distinct copayment values in the data. See Table 2 for the copayments per plan. The distribution of out-of-pocket expenditures by plan size is shown in Figure 2 (plan size is increasing from left to right). Finally, out of the 153 possible cells, we observe 153 distinct retail prices.

To control for patient heterogeneity (case mix), we controlled for age, sex, and 28 chronic conditions developed by Elixhauser et al (1998) in the AHRQ Comorbidity Software (www.ahrq.gov/data/hcup/comorbid.htm), and updated by McDonald et al, (2002). These comorbidities were obtained from the MarketScan Hospital Inpatient File and the Outpatient Services File. We use a binary indicator to control for patients with four or more of these chronic conditions.[13] Patients with multiple chronic conditions may have difficulty

[13]The 28 conditions are congestive heart failure, arrhythmias, valvular disease, pulmonary circulation disease, peripheral vascular disease, hypertension, paralysis, other neurological disorders, chronic pulmonary

complying with their medications since they may require several expensive medications. We also control individually for cardiac, pulmonary, and kidney conditions, as well as for obesity.

Next, we control for "Hospitalizations," which indicates whether the patient was hospitalized during the prescription or during the 90 days following the prescription. Such a hospitalization might give the patient less of an opportunity to refill the prescription. If the patient was not the primary insurance policy holder, but a dependent, this is recorded in the variable "Dependent." If there was more than one diabetic in the household under the same plan, this is captured with the binary indicator "Other diabetic in house." More than one diabetic in the house may make compliance less likely since the household must purchase twice the amount of drugs or more. Or, more than one diabetic in the household may make compliance more likely via a peer group effect. We control for four age categories. Note that 71% of people in the raw copayment sample and 61% of people in the coinsurance sample are retirees age 65 or over, who were insured by the firm. However, after propensity score matching, both matched samples have 61% of people as retirees. The four regions indicate the employee's geographical location. Finally, to account for factors correlated with unobservables that might affect employer choice of offering coinsurance versus copay, in the propensity score matching we also include instruments that control for market area conditions, such as income and percent white collar. These are good predictors of the local labor pool. Generosity and type of benefits offered are affected by the composition of the labor pool.[14] Area characteristics included in the propensity score model, such as log income and percent white collar workers, were taken from the Area Resource File (ARF).

disease, diabetes with chronic complications, hypothyroidism, renal failure, liver disease, peptic ulcer disease with bleeding, lymphoma, metastatic cancer, solid tumor without metastasis, rheumatoid arthritis collagen, coagulopathy, obesity, weight loss, fluid and electrolyte disorders, chronic blood loss anemia, deficiency anemias, alcohol abuse, drug abuse, psychoses, and depression.

[14]These variables performed well as instruments, in that they were significant in the propensity score modeling of copayment structure, but insignificant when included independently in the drug compliance regressions. Comparing the regressions with and without the instruments, we find that they are basically stable; while no specific test exists, this generally means that the results are robust to the specification of the propensity score (Dehejia, 2005).

4 Empirical Methods

Individuals in the data were sorted into three groups:

(0) 'non-compliers' — individuals who did not buy another anti-diabetic agent prescription to cover any of the 90 days after the first prescription ran out;
(1) 'partially compliant' individuals — individuals that buy one or more prescriptions, but those prescriptions do not cover the full 90 days (allowing a 5 days grace period after each prescription);[15] and
(2) 'fully compliant' individuals — individuals that buy one or more prescriptions to cover all 90 days (allowing a 5 days grace period after each prescription).

We estimate compliance among these three groups as an ordered logit model, with outcomes ranked, as above, as 0, 1, 2, respectively. As a secondary investigation, we also examine a continuous measure of compliance, the medicine possession ratio, using weighted least squares. The medicine possession ratio (MPR) is the ratio of days with a supply of medicine over the 90 days.[16]

Copayment Model

In Table 4, the regressions follow the specification given below in equation (9) derived from the theory in Proposition 1. That is, from equation (8), for each patient i, we can now

[15]Here we follow the pharmacological literature where it is standard to allow for a 5-7 grace period for refill continuity (e.g., Ellis et al 2004). Note that we explored the wider 7 day window but this had little effect on the results.

[16]MPR ratios are sometime used in the pharmacological literature (Rizzo and Simons, 1997; Steiner and Prochazka, 1997), but have the disadvantage of ignoring discontinuities in coverage. For this reason we focused on our discrete measures of compliance, ranked as full compliers, partial compliers, and non-compliers. The continuous analysis on MPR and the ordinal logistic analysis yielded qualitatively similar results. Compare Tables 5 and Table 6. While insulin was recently added as a possible therapeutic intervention for type 2 diabetes, this does not affect our study period and we do not include it in the MPR.

write the ordered logit model for copayments as

$$Pr(y_i = 0) = Pr(\beta C(p)_i + Z_i\zeta + \omega_i \ \leq \ \kappa_1),$$

$$Pr(y_i = 1) = Pr(\kappa_1 \ < \ \beta C(p)_i + Z_i\zeta + \omega_i \ \leq \ \kappa_2),$$

$$Pr(y_i = 2) = Pr(\kappa_2 \ < \ \beta C(p)_i + Z_i\zeta + \omega_i), \tag{9}$$

where $C(p) = c$ under copayments, and where the error term ω is logistically distributed. Note that $y_i = 0$ if the patient never complied within 90 days of finishing her last prescription; $y_i = 1$ if the patient sometimes complied, but not always; and $y_i = 2$ if the patient always complied for the 90 days. Vector Z_i is a vector of patient risk adjustors. The cutoffs κ_1 and κ_2 are estimated along with the other coefficients in Table 3. We correct the standard errors for clustering at the plan level.

Coinsurance Model

The regression in the last column of Table 4 now includes the coinsurance rate squared, r^2, according to the theory from Proposition 1. That is, from (8), for each patient i, we can now write the ordered logit model for coinsurance as

$$Pr(y_i = 0) = Pr(\beta C(p)_i + \gamma r_i^2 + Z_i\zeta + \omega_i \ \leq \ \kappa_1),$$

$$Pr(y_i = 1) = Pr(\kappa_1 \ < \ \beta C(p)_i + +\gamma r_i^2 + Z_i\zeta + \omega_i \ \leq \ \kappa_2),$$

$$Pr(y_i = 2) = Pr(\kappa_2 \ < \ \beta C(p)_i + \gamma r_i^2 + Z_i\zeta + \omega_i), \tag{10}$$

where $C(p) = r\bar{p}$ under coinsurance and where the error term ω is logistically distributed. Note that $y_i = 0$ if the patient never complied within 90 days of finishing her last prescription; $y_i = 1$ if the patient sometimes complied, but not always; and $y_i = 2$ if the patient always complied for the 90 days. Vector Z_i is a vector of patient risk adjustors. The cutoffs κ_1 and κ_2 are estimated along with the other coefficients in Table 4. We correct the standard errors for clustering at the plan level. From Proposition 1, we expect to find that

$\beta < 0$ and that $\gamma < 0$, since the distribution of illness is declining in the number of chronic conditions in our data (Figure 1).

The coefficients in the ordered logit are not marginal effects. However our main interest is in assessing the impact of a change in cost-sharing policy on compliance, changing flat copayments to coinsurance. In Table 5 we present a simulation in which the copayment and coinsurance rate are set so that the expected out-of-pocket is at the same \$9 level, the median for the data. In Table 5, we also present simulations that demonstrate the effect on the distribution of compliance via flat copayments versus coinsurance rates when the out-of-pocket is increased over the 10th, 25th, 75th, and 90th percentiles, from \$4 to \$18. Note that marginal effects for each alternative can be calculated for continuous variables. To conserve space we do not report effects for all alternatives separately, but these are available from the authors upon request. Coefficients in Table 4 can be interpreted as indicators of the effect of covariates on the relative propensity to comply.

5 Results

In Figure 3, we see that in the first week of the 90 days following the prescription, about 54% of the copayment sample fully complied. By week 4, more than 60% were fully complying. This tapers off to about 58% by the end of the 90 days. Figure 4 provides the hazard rate of compliance. For the copayment sample, about 46% of the people had not complied by the end of the first week. By the end of the 90 days, about 31% still had never complied. This corroborates the general claim of drug manufacturers that about 30% of people do not take their medication appropriately. From Figure 4, we also see that about 69% had complied for at least one week by the end of 90 days. Thus, about 15% of the initial non-compliers under copayments became partial compliers during the 90 days.

In Figure 3, we also see that people under coinsurance generally have the same behavioral pattern as the people under copayments, except that compliance is systematically about

10% lower under coinsurance. In the first week following the end of the prescription, about 44% of the coinsurance sample people fully complied. By week 4, about 50% were fully complying. This tapers off to about 48% by the end of the 90 days. In Figure 4's hazard rate of compliance, for the coinsurance sample about 56% of the people had not complied by the end of the first week. By the end of the 90 days, about 42% still had never complied. We also see that about 58% had complied for at least one week by the end of 90 days. Thus, about 14% of the initial non-compliers under coinsurance became partial compliers during the 90 days.

In Table 4, the coefficient for the out-of-pocket has the expected negative sign as predicted by the theory, indicating that cost sharing reduces compliance. Thus, the standard demand theory *out-of-pocket effect* of theory equation (8) holds for both copayments and coinsurance. The additional term for coinsurance (r^2) in Table 4 shows that coinsurance further reduces compliance beyond the effect of the out-of-pocket. This verifies the *coinsurance effect* of Proposition 1, and shows that as the coinsurance rate increases, compliance further declines under coinsurance, as predicted in equations (7) and (8). Thus, the full model of Proposition 1 holds empirically.

Other variables are of lesser interest, and were included as controls to allow us to obtain adjusted cost-sharing effects. Nevertheless, a number of results are worth noting. First, patients with 4 or more chronic conditions are less likely to comply, as predicted. Other diabetics in the household increased compliance. Next, the variable hospitalization represents interruptions in daily drug regimen, and, thus, not surprisingly, reduces compliance significantly. Finally, compliance is significantly higher for those over age 68. A possible explanation is that this is a time-price effect—retired individuals have more free time to reach a pharmacy or follow their regimen, compared with working age adults.

Sensitivity Analysis

The Table 5 simulations were based on the matched sample regressions of Table 4. Table 5 compares flat copayments to coinsurance, where the copayment and coinsurance

rate are constructed so that the expected out-of-pocket is equal for the two regimes, at \$9, the population median out-of-pocket in the matched sample. That is, the copayment is set at $c = 9$ in the matched copayment sample, and, to generate an equivalent case in the matched coinsurance sample, we took the coinsurance rate r to be $r = 9/E(p)$, the rate that would yield a \$9 out-of-pocket, on average (i.e., r=34%). Table 5 suggests that the non-compliance rate is 82% higher in the coinsurance case (48.7% versus 26.7%), as predicted by the theoretical model in Proposition 1 (since $G'' < 0$ in Figure 1 for the case of our data). The share of compliers declines by 31%, from 34.1% to 23.5% moving from flat copayments to coinsurance at the same expected out-of-pocket. Partial compliers declined from 39.2% to 27.8%.

Next, in addition to simulations at the median out-of-pocket \$9, in Table 5 we also simulate the effect on the distribution of compliance via flat copayments versus coinsurance rates when the out-of-pocket is increased over the 10th, 25th, 75th, and 90th percentiles, from \$4 to \$18. In particular, in the last column of Table 5, we simulate the percent increase from the 25th to the 75th percentile of out-of-pocket, which is equivalent to an increase from \$6 to \$11. In the flat copayment model, this increase resulted in a statistically significant 8.5 percentage point increase in the share of non-compliant persons, and a concomitant 9.8 percentage point reduction in the share of fully compliant persons. There was a statistically insignificant increase in the share of partially compliant individuals. In contrast, in the coinsurance model, an increase in the coinsurance rate that would increase the expected out-of-pocket from \$6 to \$11 corresponded to an increase from 23% to 42% in the coinsurance rate. This resulted in a statistically significant increase in the share of those who never comply, up by 25 percentage points, while the reduction in fully compliant persons was also much higher than in the copayment model, 19.7 percentage points.

To test the robustness of our ordered logit model in Tables 4 and 5 which uses only three groups—compliers, partial compliers, and never compliers—we also ran weighted least square regressions with the covariates of Table 4 but with a continuous independent variable: the medicine possession ratio, the percentage of days that the patient possessed medications

over the 90 days following the completion of the first prescription. In Table 6, we find very similar results with the medicine possession ratio. At the median out-of-pocket, \$9, the medicine possession ratio is 47% higher in the flat copayment case (63.6 versus 43.4), as predicted by the theoretical model in Proposition 1 (since $G'' < 0$ in Figure 1 for the case of our data). Simulating the percent increase from the 25th to the 75th percentile of out-of-pocket, \$6 to \$11, the medicine possession ratio decreases 12% under copayments (from 68.4 to 60.3). In contrast, it decreases by 44% under coinsurance (from 57.8 to 32.1). Thus, coinsurance has a more dramatic impact on noncompliance than does copayments when out-of-pocket increases.

As a further test of robustness, instead of using ordered logit over three outcomes (full, partial, no compliance) as in Table 4 and 5, in Table 6 we also include simulations from three different logit binary models for compliance. In the first binary model of Table 6, we code the fully and partially compliant patient as 1, and 0 if they never complied. In the second binary model, we code the fully compliant patient as 1, and 0 if they partially or never complied. In the third binary model, we use the second binary model but with partial compliers removed from the analysis. All three models exhibit the same qualitative results supporting the theory of Proposition 1: coinsurance produces significantly less compliance than copayments.

Finally, to test the robustness of the results with respect to a possible selection bias in which patients self-select into copayment plans or coinsurance plans, we reran our regressions on a subsample restricted to firms that offered no choice of health plans. Thus, out of 14 plans with copayments, 5 of these plans were offered as the only choice. Of the 3 coinsurance plans, one was offered without a choice. On this matched subsample of no choice plans, the coefficients of the key parameters were close to those of the full sample of plans. The coefficient on the "out-of-pocket" variable in the copay sample was -.13 with no choice versus -.11 in the full sample (P-value .80). In the coinsurance sample, the coefficient on the "out-of-pocket" variable in the copay sample was -.029 with no choice versus -.028 in the full sample (P-value .58). Generalized Hausman tests (run via seemingly unrelated

estimation so that we could cluster standard errors at the plan level in the test) indicated that no self-selection problems exist.[17]

6 Discussion

We examined compliance and non-compliance with drug prescription regimens in a sample of non-insulin diabetics. Diabetes represents a case in which prescription medication must be taken permanently to mitigate adverse health effects and consequently minimize future treatment costs. We found that increased cost-sharing results in lower rates of compliance and higher rates of non-compliance regardless of the cost-sharing mechanism in place. However, the negative effects of cost-sharing on non-compliance are larger in the coinsurance regime than in the copayment regime. The theory suggests that this is due to greater uncertainty in out-of-pocket costs created under coinsurance.

The implications of these results are broad, for both private employers and for government programs. First, payers may wish to reexamine benefit policies that have imposed higher levels of cost-sharing for prescription drugs, often ignoring the function of prescription drugs in prevention of complications from chronic conditions such diabetes, arterial diseases, hypertension and the like. For instance, the recent run-up in state budget deficits have forced some state-managed Medicaid programs to raise drug copayments. For low income people who are the beneficiaries of Medicaid coverage, the non-compliance effect could be larger than we estimate here. Medicare Part D, a prescription drug benefit plan for the elderly introduced in 2006, is estimated to cost more than $500 billion over 10 years and involves high copayments at certain ranges: in a so-called 'donut' type plan, beneficiaries will face a 25% coinsurance rate up to some level of spending, a 5% coinsurance rate above a certain upper limit, but a full 100% coinsurance rate in the middle range. The findings

[17] The Hausman test estimates $V(b-B)$ with $V(b)-V(B)$. For $V(b)-V(B)$ to be an admissible estimator of $V(b-B)$, there can be no clustering in the data. Since we have clustering, we use the generalized Hausman test, which, with seemingly unrelated estimation, estimates $V(b-B)$ with $V(b)-cov(b,B)-cov(B,b)+V(B)$, which is an admissible estimator.

of this study suggest that compliance in this range will be particularly low.

Second, in our empirical analysis we demonstrated that non-compliance is higher under coinsurance compared with fixed copayments, holding the *level* constant. Thus, for certain chronic conditions such as diabetes, where improved compliance leads to reduced illness, cost-savings can be attained in a budget neutral way by switching from variable coinsurance rates to flat copayment rates. Of course, coinsurance may still result in lower costs for medications in more benign settings or when use is inappropriate. This applies not only to Medicare, but also to prescription drug plans offered in the private sector. If the goal is to improve compliance and reduce cost in the long run, then many employers are moving in the wrong direction: In 2002, 19% of employers who offer prescription drug benefits to their employees switched from copayments to coinsurance at the expiration of their contracts (Encinosa, 2002). In addition, many employers are moving to consumer-driven health plans and health savings accounts, where employees face high coinsurance rates (particularly, through large deductibles). The idea is that coinsurance exposes the consumer to more of the medical price, inducing the patient to shop for lower prices (maybe lower than what the employer could shop for). In our data, we do observe lower prices for the non-Sulfonylureas diabetic drugs (like Metformin) among the coinsurance patients compared to the copayment patients ($57.01 versus $57.88), but not for the Sulfonylureas diabetic drugs ($18.21 versus $17.99). This may have been due to more price shopping under coinsurance, or may have been due to more switching to cheaper drugs, such as generics, under coinsurance. However, we find that 15% of the coinsurance sample used generics compared to 22% of the copayment sample. Future research should examine the extent of price shopping under coinsurance in greater detail.

Interestingly, anecdotal evidence suggests that other employers are beginning to recognize the compliance issue, and are revising their benefit structure accordingly. For example, Kaiser Permanente offered zero copayments for preventive care in some of their plans in 2007. In particular, Pitney Bowes, a firm with 35,000 employees, recently dropped its coinsurance rate for diabetic drugs from 50% to 10%. According to the firm, this reduced

the overall costs of care for the median diabetic by 12% (Fuhrmans, 2004). Moreover, the University of Michigan began a pilot program in 2006 in which it provides no cost or discounted diabetes medications to its employees and their dependents. There is surprisingly little literature, however, that can shed light on the optimal level of cost sharing in such plans. Chernew, Encinosa, and Hirth (2000) show that it is sometimes optimal to have negative copayments, i.e., actually offer rebates, for patients with severe chronic conditions or for individuals likely to opt for low quality treatment at the margins[18]. There is a need for further theoretical and empirical research on this issue. Future research should also examine the costs and benefits of patient cost-sharing increases in finer detail. Specifically, there is a need to develop estimates of averted treatment costs from improved compliance.

[18](Zweifel, 1995) has also examined such rebates in the German health care system.

Appendix 1

Proof of Proposition 1: First, we assume there are no boundary solutions. That is, we assume interior conditions such that $0 < s^* < 1$ and that $0 < \frac{V-rp}{e} < 1$ for all prices. Next, from (6), for any given p we expand the probability of compliance under coinsurance $G(\frac{V-rp}{e})$ in a Taylor series about the fixed point $\frac{V-rE(p)}{e}$ to get

$$G\left(\frac{V-rp}{e}\right) = G\left(\frac{V-rE(p)}{e}\right) + G'\left(\frac{V-rE(p)}{e}\right)\left[\frac{V-rp-(V-rE(p))}{e}\right] + \\ +\frac{1}{2}G''\left(\frac{V-rE(p)}{e}\right)\left[\frac{V-rp-(V-rE(p))}{e}\right]^2 + ... \tag{11}$$

Now taking the expectation E of price in (11) leads to

$$EG\left(\frac{V-rp}{e}\right) = G\left(\frac{V-rE(p)}{e}\right) + \frac{G''\left(\frac{V-rE(p)}{e}\right)r^2\sigma^2}{2e^2} + ... \tag{12}$$

Note that from (5), $G(\frac{V-rE(p)}{e}) = Prob(comply|copay)$. Also, recall that $s^* = \frac{V-c}{e} = \frac{V-rE(p)}{e}$ from (4). Thus, (12) provides the approximation in (7). Note that compliance is higher under copayments in (7) when $G'' < 0$. Also, note that $G'' < (>)0$ when G is concave (convex). Or, in other words, from Jensen's Inequality (Mood, Graybill, and Boes (1974), page 72), we know that $G(E(\frac{V-rp}{e})) > E(G(\frac{V-rp}{e}))$ holds precisely when G is concave, with the converse holding when G is convex. □

Appendix 2

A generalized Proof of Proposition 1 for the case where V varies with s: First, define benefit function $B(s) = V(s) - es$ (Appendix 1 dealt with the case $B(s) = V - es$). Thus, now $s^* = B^{-1}(C(p))$ for out-of-pocket $C(p)$. Assume that B is concave with marginal returns to benefit declining at the marginal, indifferent patient, $B'(s^*) < 0$. Then all patient with s above s^* will not comply, and the probability of compliance under out-of-pocket $C(p)$ will be defined as $\Lambda(C(p)) = G(B^{-1}(C(p)))$. Then equation (7) in Proposition 1 now generalizes to

$$Pr(comply|coinsurance) \simeq Pr(comply|copayment) + \frac{r^2\sigma^2}{2}\Lambda'', \tag{13}$$

where

$$\Lambda'' = G''(s^*) \cdot [(B^{-1})'[rE(p)]]^2 + G'(s^*) \cdot (B^{-1})''[rE(p)]. \tag{14}$$

To prove this, for any given p we expand the probability of compliance under coinsurance $\Lambda(rp)$ in a Taylor series about the fixed point $rE(p)$ to get

$$\Lambda(rp) = \Lambda(rE(p)) + \Lambda'(rE(p))[rp - rE(p)] + \frac{\Lambda''(rE(p))[rp - rE(p)]^2}{2} + ... \tag{15}$$

Now taking the expectation E of price in (15) leads to (13). Thus, from (13) and (14) we see that less compliance will occur under coinsurance if $G'' < 0$, since in the second term of the right-hand-side of (14) we have $(B^{-1})'' < 0$ since B is concave.□

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Figure 1: Distribution of States of Health and Compliance

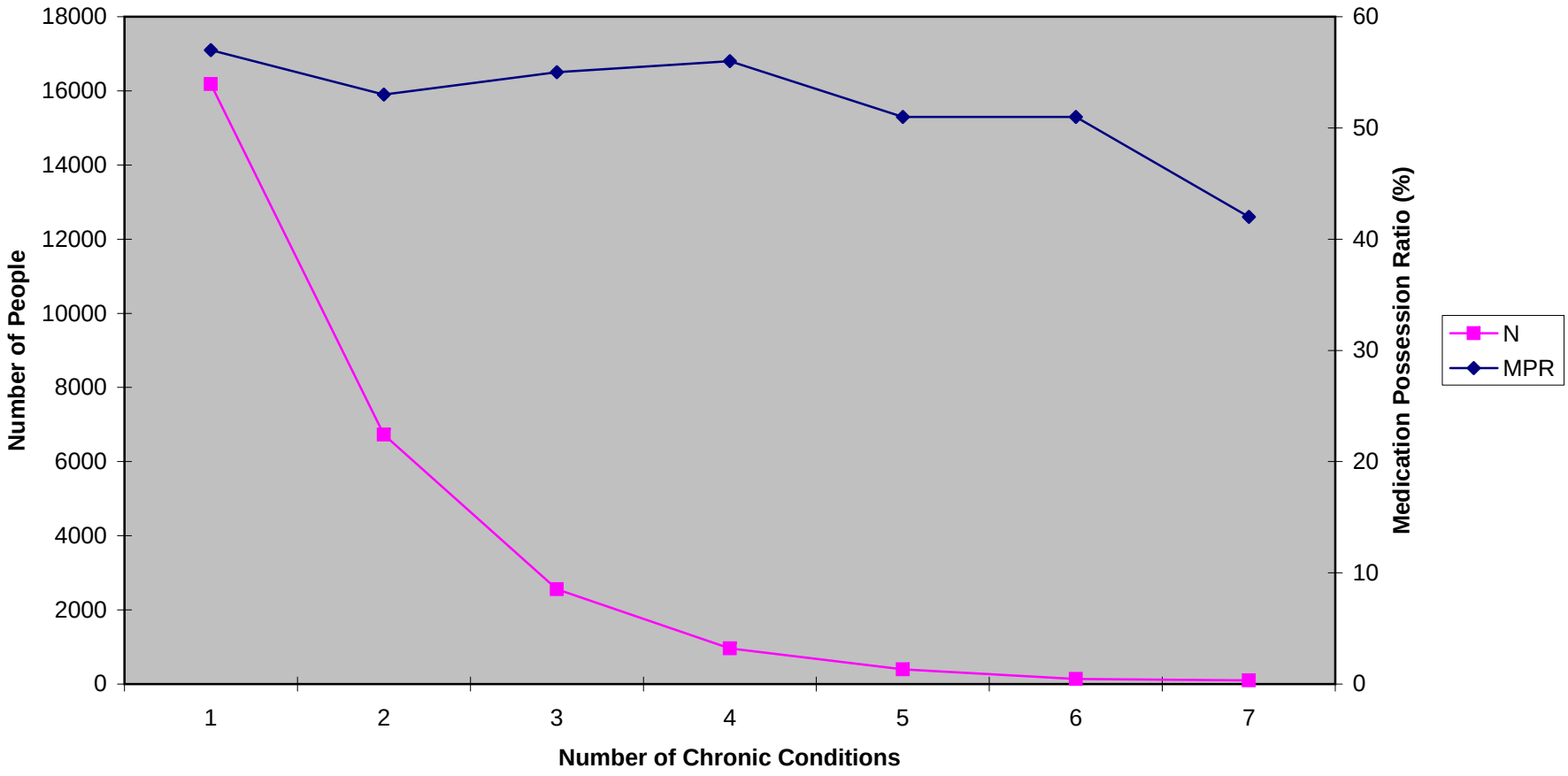

Figure 2

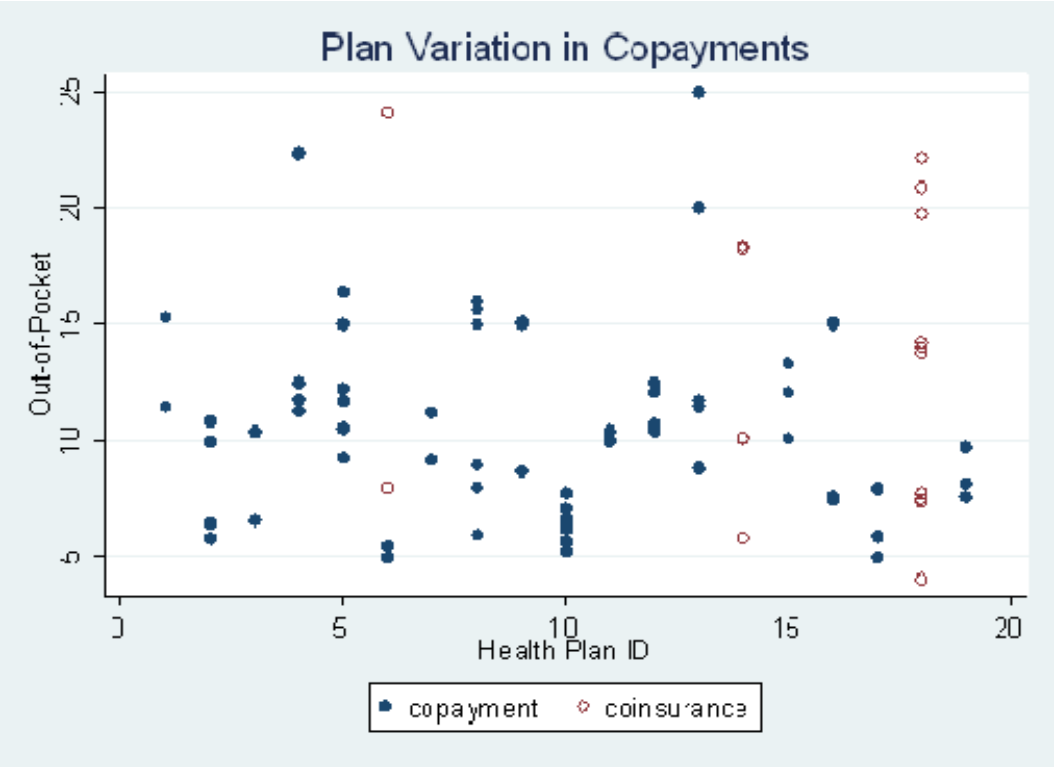
Plan Variation in Copayments
Out-of-Pocket
5
10
15
20
25
0
5
10
15
20
Health Plan ID
copayment
coinsurance

Figure 3: Rate of Weekly Compliance

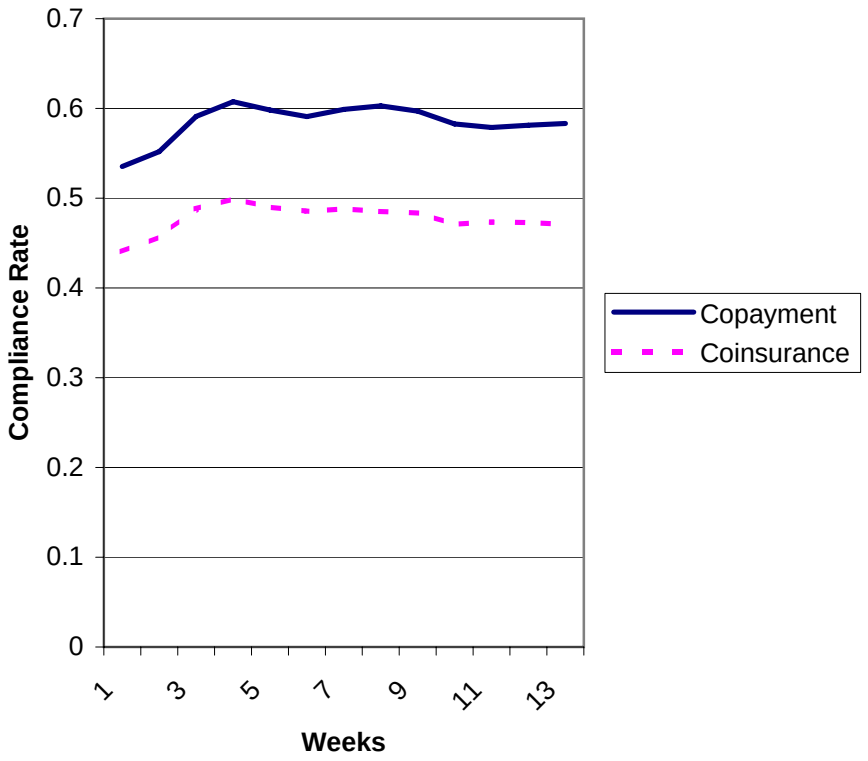

Figure 4: Compliance Hazard Rate

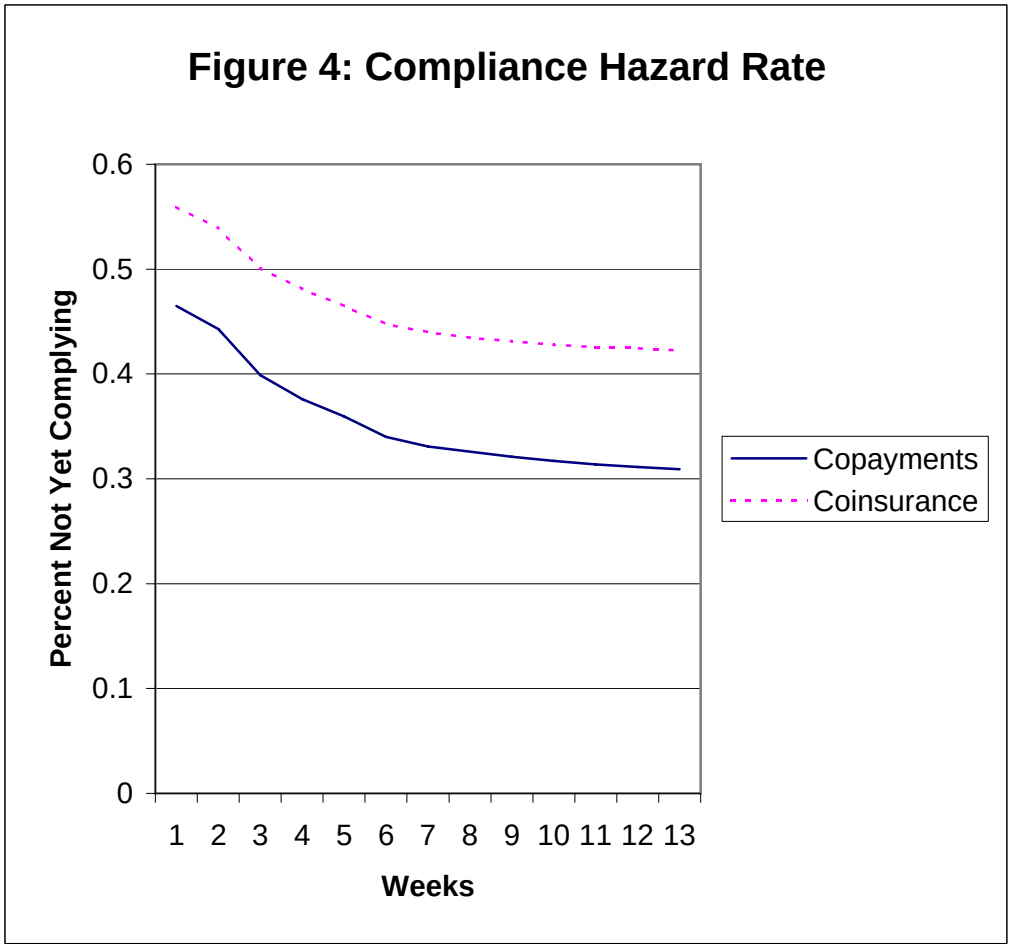

Table 1: Pharmacological Treatment of Type 2 Diabetes Mellitus[a]	
Major Metabolic Defect	Drug Therapy
Defective Insulin Secretion	*Secretagogue Therapy*
Pancreatic Beta Cells (decreased insulin secretion)	Sulfonylureas (SU) Non-SU Secretagogues (Meglitinides)
Insulin Resistance	*Insulin Sensitizer Therapy*
Skeletal Muscle (decreased glucose uptake)	Thiazolidinediones (TZD)
Liver (increased glucose production)	Biguanides (Metformin) TZD
Adipose Tissue (increased lipolysis)	TZD
Carbohydrate Absorption	Drug Therapy
Small Intestines	*Alpha-Glucosidase Inhibitors (AGI)*

[a] *Source: Inzucchi (2002).*

Table 2: The 17 Heath Plans and Their Diabetic Copayment Levels			
	Mean	Min	Max
Copayment Plans			
Plan 1	$5.01	$5.00	$5.50
Plan 2	6.88	5.00	8.00
Plan 3	8.03	6.60	10.40
Plan 4	11.93	6.00	16.00
Plan 5	10.08	7.50	15.10
Plan 6	14.03	11.50	15.30
Plan 7	11.70	8.70	15.10
Plan 8	10.12	9.20	11.20
Plan 9	10.25	10.00	10.50
Plan 10	10.36	8.80	25.00
Plan 11	11.14	10.10	13.30
Plan 12	6.41	5.30	7.80
Plan 13	8.39	7.60	9.70
Plan 14	16.89	11.30	22.40
Coinsurance Plans			
Plan 15 (6% coinsurance)	$14.90	$8.00	$24.10
Plan 16 (10% coinsurance)	13.08	4.10	22.20
Plan 17 (18% coinsurance)	12.52	5.90	18.40

Note: There 75 distinct copayment values and 153 distinct retail prices across plans.

Table 3: Descriptive Statistics[a]				
	Raw Sample		Matched Sample	
Variables	Copayment	Coinsurance	Copayment	Coinsurance
Never Comply	.309	.422	.318	.422
	(.462)	(.494)	(.466)	(.494)
Partially Comply	.321	.289	.363	.289
	(.467)	(.453)	(.481)	(.453)
Always Comply	.369	.289	.319	.289
	(.483)	(.453)	(.466)	(.453)
Average Out-of-Pocket[b]	$8.586	$13.015	$12.288	$13.015
	(2.384)	(6.370)	(5.423)	(6.370)
Average Coinsurance Rate	.403	.309	.454	.309
	(.087)	(.022)	(.108)	(.022)
4 or more chronic conditions	.029	.008	.011	.008
	(.167)	(.089)	(.104)	(.089)
Other diabetic in house	.086	.059	.071	.059
	(.280)	(.236)	(.256)	(.236)
Hospitalization	.070	.060	.086	.060
	(.254)	(.237)	(.281)	(.237)
Age	67.309	64.335	64.523	64.335
	(12.527)	(12.703)	(17.509)	(12.703)
Female	.499	.543	.506	.543
	(.500)	(.498)	(.500)	(.498)
Dependent	.268	.283	.317	.283
	(.443)	(.451)	(.465)	(.451)
Cardiac	.115	.069	.088	.069
	(.319)	(.254)	(.283)	(.254)
Pulmonary	.057	.036	.046	.036
	(.231)	(.187)	(.209)	(.187)
Kidney	.020	.016	.018	.016
	(.139)	(.126)	(.131)	(.126)
Obese	.014	.000	.000	.000
	(.117)	(.021)	(.017)	(.021)
North East	.283	.003	.003	.003
	(.450)	(.051)	(.052)	(.051)
North Central	.363	.080	.045	.080
	(.481)	(.272)	(.206)	(.272)
South	.311	.912	.945	.912
	(.463)	(.283)	(.228)	(.283)
West	.043	.005	.008	.005
	(.203)	(.070)	(.087)	(.070)
Excluded Market Area Variables				
Income	$29,290	$24,866	$24,587	$24,866
	(7,758)	(7,082)	(6,573)	(7,082)
Percent White Collar	.600	.540	.532	.540
	(.468)	(.937)	(.940)	(.937)
Number of Observations	20,464	6,537	6,537	6,537

[a] Standard deviations are in parentheses. Matching of samples was done by propensity score matching. The excluded market variables are used only in the propensity score.

[b] Based on 135 plan x period x drug class (clinically indicated) cells.

TABLE 4: ORDERED LOGIT ESTIMATES OF COMPLIANCE[a]			
	Flat Copayments		Coinsurance
Independent Variables:	Raw Sample	Matched Sample	Raw Sample/Matched Sample
Average Out-of-Pocket	-0.070*	-0.106**	-0.028***
	(0.040)	(0.042)	(0.002)
Coinsurance Squared	--	--	-9.903*
			(5.587)
4 or more chronic conditions	-0.129**	0.324*	-0.269***
	(0.052)	(0.183)	(0.061)
Other diabetic in house	0.182*	0.425	0.034
	(0.099)	(0.471)	(0.034)
Hospitalization	-0.350***	-0.042	-0.215***
	(0.049)	(0.322)	(0.040)
Age 68-73	1.833***	1.813***	2.479***
	(0.312)	(0.222)	(0.023)
Age 74-80	1.839***	1.762***	2.460***
	(0.327)	(0.260)	(0.005)
Age 81+	1.721***	1.331***	2.447***
	(0.341)	(0.348)	(0.052)
Female	-0.065*	-0.072	-0.141***
	(0.035)	(0.203)	(0.053)
Dependent	0.079	-0.037	-0.078***
	(0.080)	(0.315)	(0.017)
Cardiac	0.171***	0.372	0.141***
	(0.063)	(0.316)	(0.043)
Pulmonary	-0.154**	-0.075	-0.149
	(0.074)	(0.297)	(0.128)
Kidney	-0.118**	-0.316*	0.050
	(0.049)	(0.173)	(0.040)
Obese	-1.443***	-29.820***	-27.819***
	(0.463)	(0.812)	(0.986)
K1	-0.548	-0.717	-0.254
	(0.634)	(0.749)	(1.435)
K2	1.268	1.242	1.461
	(0.607)	(0.575)	(1.500)
WaldX2(df)	81,442(16)	314,986(14)	1,464(3)
Psuedo R2	0.12	0.14	0.18
Number of Observations	17,802	6,537	6,537

[a] *Robust standard errors in parentheses are corrected for clustering at the plan level. Three region indicators are not shown.. Dependent variable is ordered as: 2 if Always Comply, 1 if Partially Comply and 0 if Never Comply.*** Significant at 99%.** Significant at 95%.* Significant at 90%*

Table 5: Simulated Percent Change in Compliance Associated with an Increase in Cost-Sharing[a]						
Out-of-Pocket Percentiles:	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Change in Compliance from 25th to 75th percentile
Compliance Levels:						
Under Copayments:						
Copayment:	$4	$6	$9	$11	$18	
Never Comply	0.188	0.218	0.267	0.303	0.444	0.085*** (39%)
Partially Comply	0.370	0.381	0.392	0.393	0.367	0.012 (3%)
Always Comply	0.442	0.401	0.341	0.303	0.189	-0.098*** (-24%)
Under Coinsurance:						
Expected Out-of-Pocket:	$4	$6	$9	$11	$18	
Never Comply	0.286	0.350	0.487	0.600	0.951	0.250*** (71%)
Partially Comply	0.302	0.299	0.278	0.246	0.039	-0.053*** (-18%)
Always Comply	0.413	0.351	0.235	0.154	0.010	-0.197*** (-56%)

[a] The compliance distributions give the probability of being in each of the three compliance categories. Results are simulated from regressions in Table 4. The percentage change from the 25th to 75th percentile is in parentheses.
**** Significant at 99%. ** Significant at 95%. *Significant at 90%.*

Table 6: Sensitivity Analysis: Alternative Compliance Measures Simulated Percent Change in Compliance Associated with an Increase in Cost-Sharing[a]						
Out-of-Pocket Percentiles:	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Change in Compliance from 25th to 75th percentile
Under Copayments:						
Copayment:	$4	$6	$9	$11	$18	
MPR	0.714	0.684	0.636	0.603	0.484	-0.081 (-12%)
Binary Models						
Full or Partial Compliance	0.811	0.785	0.743	0.715	0.613	-0.070 (-9%)
Full Compliance	0.501	0.451	0.379	0.334	0.199	-0.117 (-26%)
Fully Complied vs Never Compiled	0.693	0.651	0.587	0.544	0.406	-0.107 (-16%)
Under Coinsurance:						
Expected Out-of-Pocket:	$4	$6	$9	$11	$18	
MPR	0.648	0.578	0.434	0.321	0.028	-0.257 (-44%)
Binary Models						
Full or Partial Compliance	0.760	0.685	0.538	0.431	0.047	-0.254 (-37%)
Full Compliance	0.376	0.339	0.269	0.216	0.060	-0.123 (-36%)
Fully Complied vs Never Compiled	0.534	0.478	0.381	0.314	0.078	-0.164 (-34%)

[a] *MPR is the medical possession ratio, the percentage of days in the year with compliance. "Full or Partial Compliance" equals 1 if always or sometimes complied and 0 if never complied. "Full Compliance" equals 1 if always complied and 0 otherwise. "Fully Complied vs Never Compiled" is 1 if fully complied and 0 if never complied, with partial compliers removed. Results are simulated from regressions. The percentage change from the 25th to 75th percentile is in parentheses and is statistically significant at the 99% level.*