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Substitution, Spending Offsets, and Prescription Drug Benefit Design

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Abstract

Many U.S. employers have recently adopted less generous prescription drug benefits. In addition, in 2006 the U.S. began to offer prescription drug insurance to approximately 42 million Medicare beneficiaries. We used data on individual health insurance claims and benefit data from 1997 to 2003 to study how changes in consumers' co-payments for prescription drugs affect use of and expenditure on prescription drugs, inpatient care, and outpatient care. We analyzed the effects both in the year of the co-payment change and in the year following the change. Our results show that increases in prescription drug prices reduce both use of and spending on prescription drugs. They also show that consumers substitute the use of outpatient care for prescription drug use and that about 35% of the expenditure reductions on prescription drugs are offset by increases in other spending.

KEYWORDS: pharmaceutical, drug, demand, copay, copayment, benefit, offset, spending

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1. Introduction

In the past 15 years, national spending on prescription drugs has grown dramatically, outpacing the growth rate of hospital spending and physician spending.[1] In response, many health insurance plans have reduced the generosity of their prescription drug benefits. Ostensibly benefit designers are seeking to reduce drug spending by increasing the price faced by consumers, the co-payment.

A number of studies have investigated the relationship between cost sharing and spending on drugs (Joyce et al., 2002; Goldman et al., 2004; Huskamp et al., 2003; Soumerai, Ross-Degnan, and Gortmaker, 1987; Soumerai et al., 1991; Harris, Stergachis, and Ried, 1990; Johnson et al., 1997; Tamblyn et al., 2001; Motheral and Fairman, 2001). Almost all of these studies found that higher cost sharing reduces pharmaceutical use. In addition, some studies found that higher cost sharing results in worsened health status (Johnson et al., 1997) and increased adverse health events, such as emergency room visits, nursing home admissions, and hospital admissions (Soumerai et al., 1991; Tamblyn et al., 2001; Balkrishnan et al., 2001; Goldman, Joyce, and Karaca-Mandic, 2006). These findings suggest that a reduction in drug spending may come with unintended negative health and cost consequences.

Several authors have addressed substitution among types of medical care. Davis and Russell (1972) and Helms, Newhouse, and Phelps (1978) studied substitution between inpatient and outpatient care. Balkrishnan et al. (2001) studied the effects, in a Medicare HMO, of increased cost sharing for prescription drugs and found a consequent 25.2% increase in inpatient admissions. Tamblyn et al. (2001) found that a reduction in "essential" drug use induced by a co-payment rise is associated with increased adverse health events, such as hospitalizations. Duggan (2005) found no substitution between anti-psychotic drugs and inpatient psychiatric care. Goldman, Joyce, and Karaca-Mandic (2006) found that an increase in the co-payment for cholesterol-lowering drugs decreases the use of these drugs among those who start therapy and increases emergency room and inpatient hospital use. Lichtenberg (2000, 2002, 2007) found that differences in the quantities and types of drugs used by patients are correlated with differences in the use of other categories of health care: patients who use more and newer drugs consume less inpatient care.

Becker (1965) provides a theoretical framework for analyzing the determinants of health-related behaviors. In this approach, prescription drugs are one of many inputs to a health production function. Drugs and other medical goods, such as physician visits and hospital care, may be substitutes or complements. This theory suggests that to the extent these other inputs are

[1] See our discussion in Section 2.

substitutes (complements) for drugs in producing health, increases in drug prices will result in increases (decreases) in the consumption of other medical goods.

Grossman's (1972) health capital theory is a dynamic extension of Becker's model. In this theory, individuals inherit an initial stock of health capital that depreciates over time and can be increased by investment. Gross investments in health capital are produced by such inputs as medical care, diet, and exercise. Thus, the effects that changes in input prices have on consumers' demand for medical care may have a dynamic component through their effects on health capital.

Taken together, these theories suggest that changes in drug prices will have effects not only on the demand for drugs, but also on the demands for substitute and complementary services. They also suggest that there will be a dynamic aspect to the effects of changes in drug prices. Adjustment will occur not instantaneously but over time. For example, if an increase in drug co-payments causes people being treated for hypertension to fall out of compliance with their drug therapy, they may be more likely to suffer heart attacks, strokes, and other complications over time, leading to hospitalization, physician care, additional medication, and higher health care spending.

We used a large panel dataset of health insurance claims and benefit design information to identify the effects on drug spending, outpatient spending, and inpatient spending of changes in individuals' employer-provided prescription drug benefits. This study differs from previous work in that we analyzed dynamic adjustment by consumers; explicitly controlled for selection (via fixed effects); used a large, national dataset; and addressed substitution between drugs and other types of health care using comprehensive measures of inpatient and outpatient quantity and spending.

There are three central findings. First, we found strong, negative own-price effects for drugs. Rising co-payments are followed by reduced consumption of drugs. Second, we found substantial substitution between prescription drug use and the use of outpatient care. Increases in out-of-pocket drug prices lead not only to decreases in the demand for drugs, but also to sizeable increases in the demand for and spending on outpatient care. We did not find detectable changes in inpatient spending as a result of increases in drug co-payments. Third, we found strong dynamic own-price effects for drugs and dynamic substitution effects for outpatient care. The dynamic price effects were substantially larger than the contemporaneous effects.

This paper is organized as follows. Section 2 provides relevant institutional facts and findings from prior literature. The data used in the study are described in Section 3. Section 4 describes the empirical strategy, including estimation methods, and Section 5 discusses our results. Finally, Section 6 contains a summary and conclusions.

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2. Background

Retail drug spending, at $200.7 billion[2] in 2005, is the third largest category of health care spending, behind hospital and physician services. Between 1990 and 2005, retail drug spending rose just under fivefold, from $40.3 billion to $200.7 billion, while personal health spending overall rose a little under threefold, from $607.5 billion to $1,661.4 billion (Centers for Medicare and Medicaid Services, 2007). In response to these increases in drug expenditures, many employers and insurance plans imposed greater cost sharing on patients for the use of prescription drugs.

By far the most common form of cost sharing for prescription drugs is a menu of co-payments. Drugs are divided into groups called "tiers," and each drug in a given tier has the same co-payment. In a two-tier plan, consumers pay a lower co-payment for generic drugs and a higher co-payment for branded drugs. In a three-tier plan, a further distinction is made between "preferred" and "non-preferred" branded drugs. There is a higher co-payment for non-preferred branded drugs. A typical co-payment schedule for a three-tier plan is $5 for each generic drug prescription, $10 for preferred branded drugs, and $25 for non-preferred branded drugs. Moreover, starting in the late 1990s, insurance plans further differentiated co-payments based on whether drugs were purchased at walk-in pharmacies ("card-plan" purchases) or at mail-order pharmacies. The mail-order part of the plan typically requires that a 90-day supply of a drug be purchased at one time. Co-payments are set so that prescriptions purchased by mail order cost less per day than do card-plan purchases.

These changes led to an increase in out-of-pocket payments by consumers over time. According to statistics from the Kaiser Family Foundation and the Health Research and Educational Trust (HRET) (2006), the average co-payment for generic drugs increased from $7 per prescription to $11 per prescription (a 57% increase) from 2000 to 2006 for individuals with employer-sponsored health plans. During the same period, co-payments per prescription for preferred branded drugs increased from $13 to $24 (an 85% increase), and those for non-preferred branded drugs increased from $17 to $38 (a 124% increase). Recently, a few drug plans (about 5%) have added a fourth tier of drugs, and in 2006 the average price in that tier was $63. Finally, these estimates understate the true increase in average out-of-pocket costs, since, over time, drug plans have been increasing both the within-tier prices and the number of tiers. For example, in 2000 the distribution of workers among one-, two-, three-, and four-tier plans was 22%, 49%, 27%, and 0%, respectively, with 2% in other types of plans. In 2006, the distribution of workers in these tiers was 8%, 16%, 69%, and 5%, respectively, with 2% in others.

[2] We use the U.S. definition of "billion," meaning one thousand million.

3. Data

We used data from the Thomson Healthcare[3] MarketScan database. MarketScan is the largest private-sector health care database in the U.S., containing the paid claims of more than 7 million privately insured individuals and over $13 billion in annual health care expenditures. Thomson contracts with over 40 large employers for the submission of health insurance data for their employees. Neither employers nor health plans are identified by name in the database. The database contains longitudinal data for each person: person and family identifiers; enrollment history; use of inpatient care, outpatient care, and prescription drugs; health expenditure; and detailed health insurance coverage information.

We linked information from five different files in the MarketScan database from 1997 to 2003: (1) the enrollment file, which contains patients' demographics and detailed information on their health plan enrollment history; (2) the employer benefit plan design file, which contains summary benefit descriptions for major medical and prescription drug benefits for many health plans; (3) the hospital inpatient claims file, which contains individual hospital claims aggregated to the level of the hospital stay and provides information on diagnosis, treatment, and length of stay, as well as basic payment information; (4) the outpatient service claims file, which contains individual outpatient claims aggregated to the level of each outpatient visit with information on diagnosis, treatment procedures, and payment; and (5) the outpatient pharmaceutical claims file, which contains a claim for each prescription filled by each person with information on days of prescription drug supplied, national drug codes, therapeutic classes, and payment.

3.1 Sample Selection

In each year from 1997 to 2003, more than 40 individual employers contributed data to the MarketScan databases. However, not every employer submitted all five files to Thomson in each year. In our empirical work, we estimated models with dynamic price effects (one lag) and person-specific fixed effects. This required at least three consecutive years of information. Therefore, we selected from the database only those firms that had complete information from each of the five files for at least three consecutive years. After applying these requirements, 16 employers remained.[4]

Of these 16 employers, two used drug co-insurance and the other 14 used co-payments. For simplicity's sake, we limited our analysis to the drug plans employing co-payments, which represent the most common benefit design for

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[3] Thomson Healthcare was formerly known as Medstat.

[4] Most firms were lost because they did not submit drug data. For example, in 1997, only 19 of 53 employers had prescription drug claims data; in 2000, only 24 of 45; in 2003, 38 of 45.

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pharmaceuticals (Kaiser Family Foundation and HRET, 2006). Next, some of the information for prescription drug benefits and medical benefits in the employer benefit plan design file was missing or inaccurate. We deleted firms with missing or unclear insurance benefit information from our analysis sample, thereby losing an additional three firms.

Eleven employers had three consecutive years of full information, clear insurance benefit information, and co-payments as their drug cost-sharing mechanism. These 11 employers offered multiple insurance plans of varying generosity. Of these 11, nine had a single, uniform prescription drug benefit plan—that is, all employees had identical prescription drug plans at any given time. We focused on the plans of these nine employers. For consumers covered by these firms, any change in consumer out-of-pocket price for prescription drugs resulted not from the employees switching drug plans, but from the employers uniformly changing the benefits of all their employees. At last we had 97 insurance plans from nine large employers that were covering a total of 1,304,687 consumers. On average, there were 4.3 years of data from each employer.

We restricted our selection of individual consumers by examining only those who had been continuously enrolled for at least three years at some point during the 1997–2003 period.[5] This selection criterion ruled out about 56% of the individuals. Last, people older than 65 were excluded because of the complexities introduced by Medicare coverage, potential outside Medigap coverage, and coordination-of-benefits issues. Finally, we had a panel dataset of 1,713,879 person-years from 526,086 consumers who were in 97 different insurance plans at nine different employers spanning the seven-year period from 1997 to 2003.

Given all the observations eliminated by the inclusion criteria, there was a natural concern about the representativeness of the data in the analysis sample. We compared demographic and spending variables for people in our analysis sample with those for the full sample in the MarketScan database and the employer-insured U.S. population. Benchmarking information for the employer-insured U.S. population was derived from the Agency for Healthcare Research and Quality's Medical Expenditure Panel Survey (MEPS). MEPS contains a large number of demographic, economic, and health-related measures from a large-scale, nationally representative probability sample of the U.S. civilian, non-institutional population.[6] Figure 1 shows our age-comparison results, which suggest that the age distribution in the MarketScan sample (excluding those older than 65) represents the employer-insured U.S. population well except for underrepresenting age group 25–44 by 6.8% and overrepresenting age group 55–64 by 4%. Figure 2 shows the results for geographic location. As can be seen, the

[5] "Continuously enrolled" here means continuously enrolled in any of the firm's health plans. We did not drop people who switched among health plans.
[6] See http://www.meps.ahrq.gov.

Figure 1: Age Representation of Analysis Sample

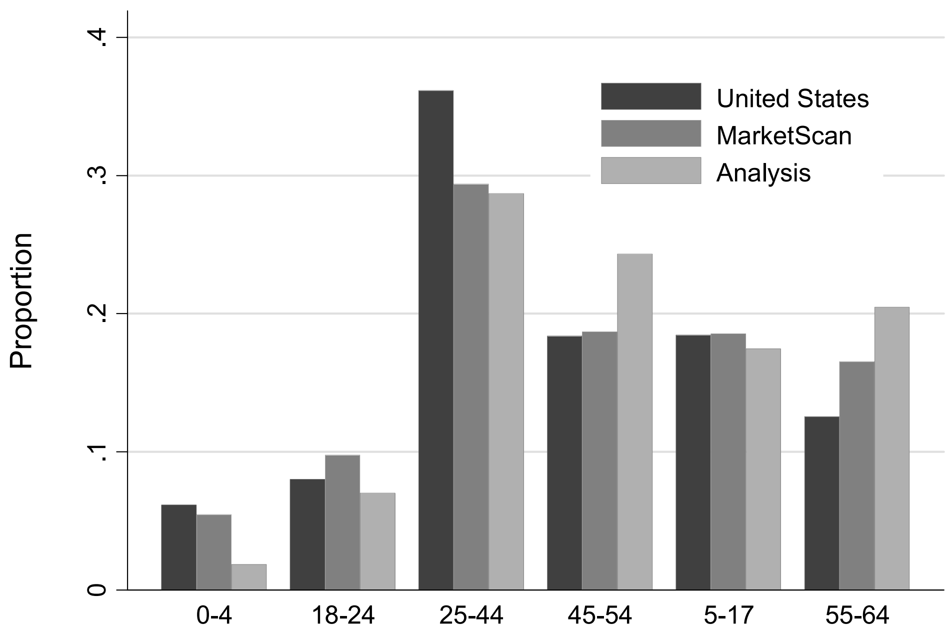
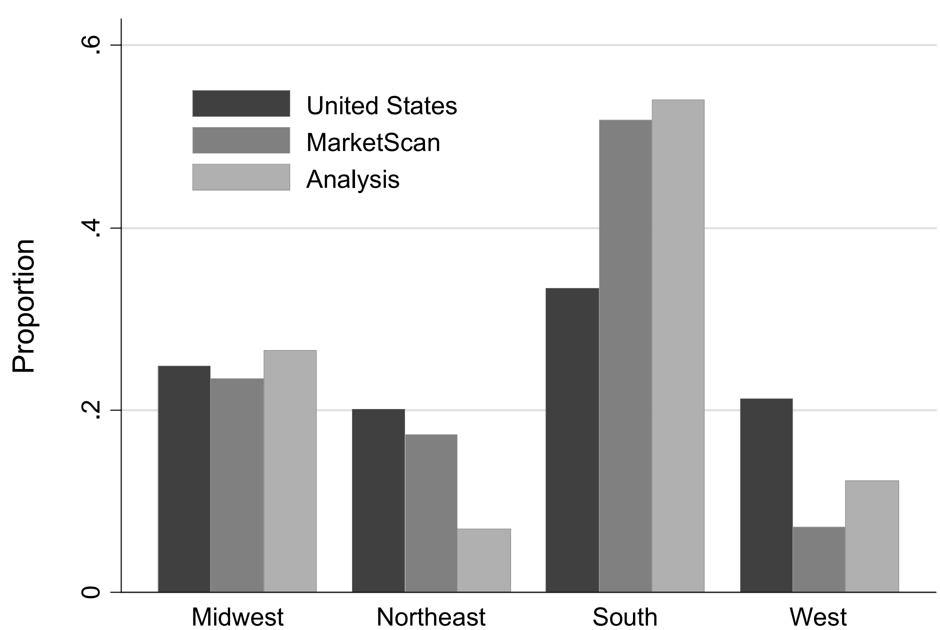


Figure 2: Geographic Representation of Analysis Sample



MarketScan sample and our analysis sample are less representative in terms of regional distribution. The South is overrepresented in these two samples, and the Northeast and West are underrepresented.

Figures 3 and 4 show the representativeness of drug spending and health care spending. They indicate that the three samples followed similar trends in per capita total spending and pharmaceutical spending, but that enrollees in the MarketScan sample on average spent \$146 more for prescription drugs and \$300 more for all types of medical care. For our analysis sample, enrollees on average spent \$380 more for prescription drugs and \$945 more for all types of medical care, compared with an average employer-insured U.S. person.

One might wonder to what degree differences in spending between our analysis sample and the U.S. population arise from differences in prices and in quantity. Consider the line labeled “United States, adjusted” in Figure 3. This line shows what the average drug spending in the MEPS employer-covered sample would have been had individuals in the MEPS sample paid the same drug prices that members of the MarketScan population paid on average in the same year. That is, we calculated (for each National Drug Code) average payments for each drug in each year in the MarketScan data and applied them to the quantities purchased in the MEPS sample. This adjustment had approximately no impact on drug spending in the MEPS sample; therefore, we conclude that differences in drug spending in the two samples arose largely from differences in drug quantity.

Figure 3: Drug Spending Representativeness

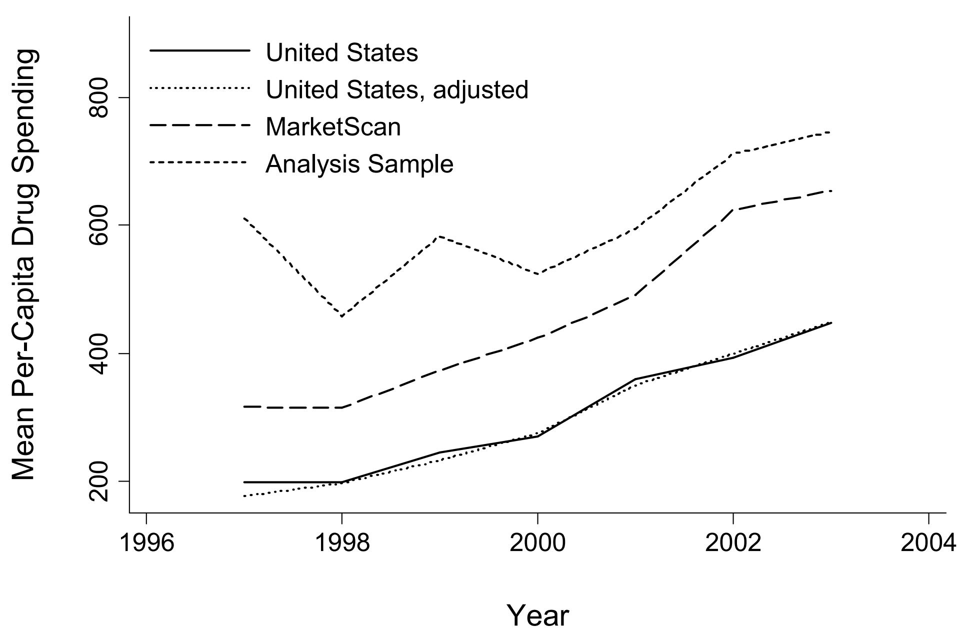
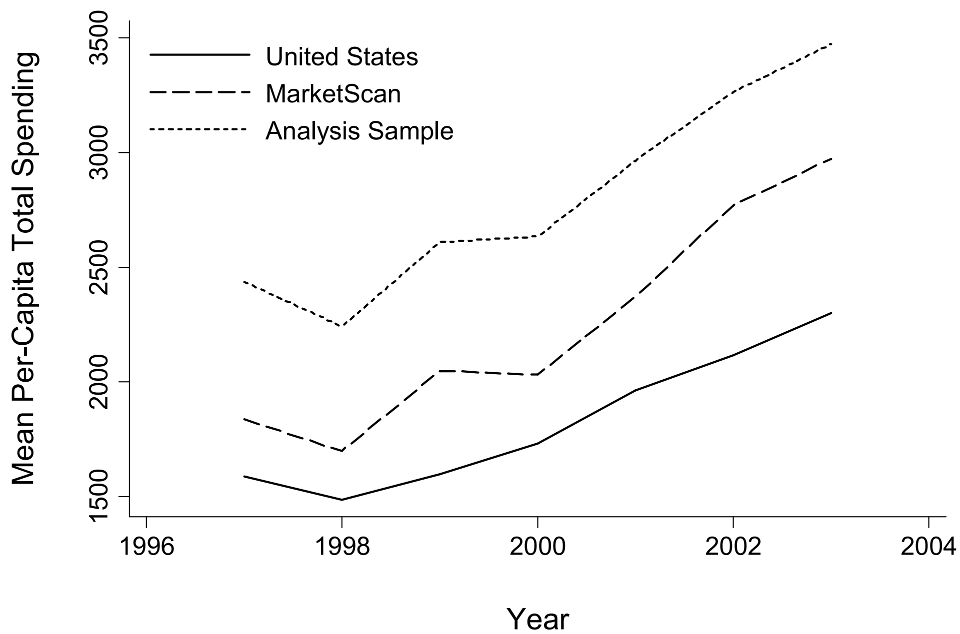


Figure 4: Health Care Spending Representativeness



Similarly, Figure 5 shows the difference in the number of inpatient days per capita between our analysis sample and the MEPS sample. This measure also indicates that our analysis sample uses more resources. Owing to potential differences in definitions and organization of the outpatient data, we did not perform a similar comparison on those data.

We also examined differences in the "incidence" of several important health conditions in the MEPS sample and our analysis sample: heart disease, stroke, hypertension, high cholesterol, asthma, and diabetes. The incidence measures were inferred from the ICD-9CM diagnosis codes in the inpatient and outpatient claims data in each sample. A person was defined as incident with the named condition in one year if there was a relevant diagnosis code in that year.[7] For each condition in each year, incidence was higher in our sample than in the MEPS sample. Figure 6 shows the combined incidence of the six conditions.

3.2 Measures

Our dependent variables were quantity of and total spending on prescription drugs, outpatient care, and inpatient care. For prescription drugs, quantity is defined as the sum of days supplied from all prescriptions filled from a particular

[7] Note that we did not use initial diagnoses for our incidence measures, so our measures are not really "incidences" as that term is conventionally understood.

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Figure 5: Inpatient Days Representativeness

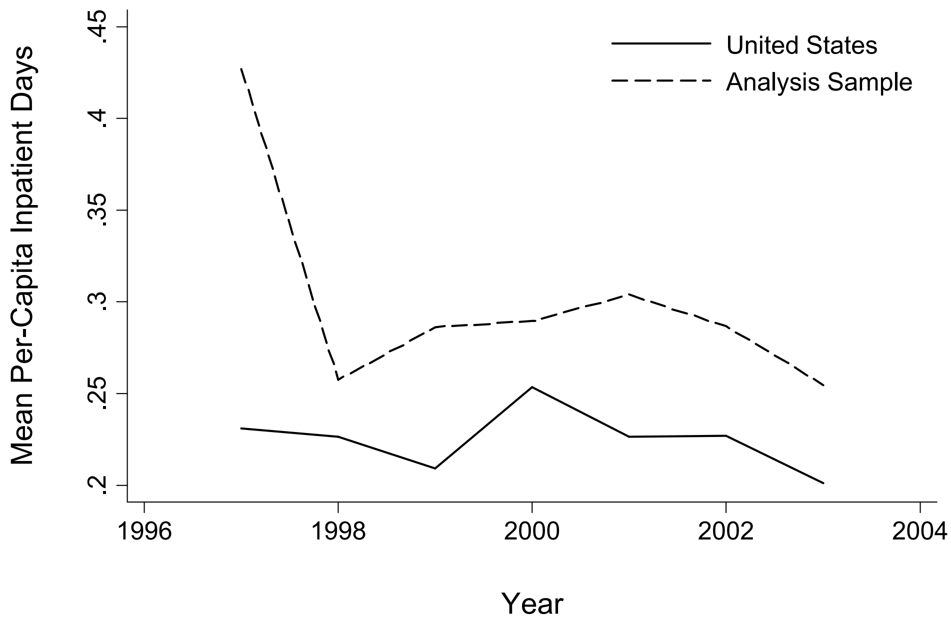
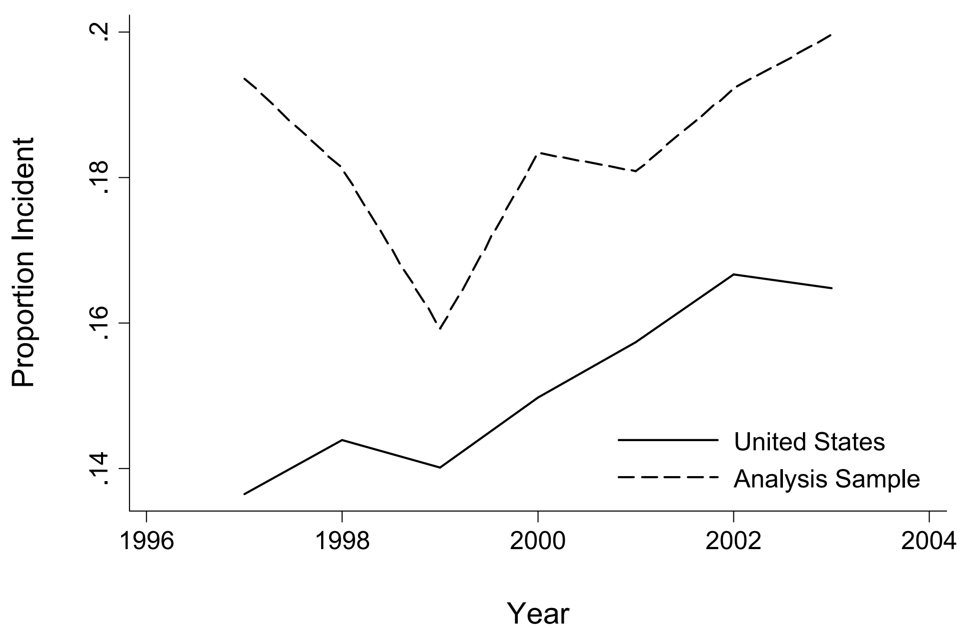


Figure 6: Comparative Disease "Incidence"



year for a patient.[8] Similarly, quantity of outpatient services is the total number of outpatient visits, and quantity of inpatient services is the total number of inpatient admissions.[9]

Total spending on prescription drugs, outpatient services, and inpatient services was calculated as the yearly spending per enrollee. This measure of spending is the sum of the spending by the insurer in the database and the required out-of-pocket spending by the insured person. We were not able to observe whether consumers actually made their out-of-pocket payments; neither were we able to observe the operations of coordination-of-benefits.

Since we used an individual fixed effects (FE) model in our estimation (see Section 4), only time-varying socio-demographic variables were used. The effects of time-invariant variables, such as race, sex, and education, were absorbed in the individual FE. We used indicators of retirement status, a set of individual FE, and a set of year FE. Because we entered both individual and year FE, we could not also enter age into our estimating equations. We did want, however, to allow spending to grow at different rates for people in different age groups, so we constructed a set of interactions between dummies for age category and a linear time trend. We separated people into seven age categories: 0–10 years, 11–18, 19–29, 30–39, 40–49, 50–59, and 60–64.

Our primary independent variable of interest was the out-of-pocket price faced by consumers for prescription drugs. In the presence of health insurance, the prices faced by a consumer for health services are determined by the consumer's health plan benefit design. Ideally, one would like to include all relevant aspects of the prescription drug benefit design in the analysis. There are six variables describing the benefit design in the MarketScan database: generic co-payment, preferred branded co-payment, and non-preferred branded co-payment, separately for the two types of purchases—card plan and mail order. While this is a rich source of descriptive information, these measures are highly collinear; therefore, it is not possible separately to identify their effects in a regression. Further, 18 changes in drug benefit design occur in the data, making it highly unlikely that we could identify parameters for six variables describing the drug benefit.

Thus, we constructed an out-of-pocket price index for prescription drugs for each health plan in each year. For each plan year, the price index is a weighted average of the out-of-pocket co-payments for that plan's tiers: the generic co-payment, the preferred branded co-payment, and the non-preferred branded co-payment. For a plan with only two tiers, we used that plan's branded co-payment as both the preferred and the non-preferred branded co-payment. In addition, since plans often specify different co-payments for card-plan and mail-order

[8] Our results are similar if we define "quantity" as the number of prescriptions filled.
[9] We also ran the analysis using inpatient days as the quantity measure and obtained similar results.

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purchases, we differentiated between those two modes of delivery in the price index. The formula for the price index for plan *j* in time *t* is

$$P_j^t = Copay_{j,G}^{t,Card} * W_{Card,G} + Copay_{j,PB}^{t,Card} * W_{Card,PB} + Copay_{j,NPB}^{t,Card} * W_{Card,NPB}$$
$$+ Copay_{j,G}^{t,Mail} * W_{Mail,G} + Copay_{j,PB}^{t,Mail} * W_{Mail,PB} + Copay_{j,NPB}^{t,Mail} * W_{Mail,NPB} \quad (1)$$

Plan *j*'s co-payments for one prescription at a walk-in pharmacy for, respectively, generic, preferred branded, and non-preferred branded drugs are $Copay_{j,G}^{t,Card}$, $Copay_{j,PB}^{t,Card}$, and $Copay_{j,NPB}^{t,Card}$. For a mail-order prescription, the co-payments are $Copay_{j,G}^{t,Mail}$, $Copay_{j,PB}^{t,Mail}$, and $Copay_{j,NPB}^{t,Mail}$. The $W_{m,n}$ are quantity-based weights for generic, preferred branded, and non-preferred branded drugs for card-plan and mail-order purchases, calculated using prescription drug claims data for all enrollees in all the years in the nine study firms. For example, the weight on the generic mail-order co-payment, $W_{Mail,G}$, is the proportion of prescriptions in our whole sample (all firms and years) that are generic drugs purchased by mail order.

Table 1 contains the weights for the six categories. For example, the table shows that the weight on the generic mail-order co-payment is 0.0603, meaning that 6.03% of all prescriptions in our data are for generics filled by a mail-order pharmacy. This price index changes for a consumer only when the consumer's employer changes its prescription drug benefit design.

Because of the potential for input substitution in the production of health, the demand equations for each type of medical care are functions of drug prices and the prices of other medical services. Insurance benefits are more complicated for outpatient and inpatient services than for prescription drugs. Common cost-sharing devices for medical services take the form of a combination of deductibles, co-insurance rates for spending above a deductible, a co-payment for one physician office visit, and a stop-loss limit beyond which consumers pay no more. The budget sets for these medical services are therefore complicated and nonlinear. It is difficult to construct a single price measure for these services that will correctly reflect the true out-of-pocket prices consumers pay. Instead, we

Table 1: Co-payment Index Market Basket Weights

	Card Plan	Mail Order
Generic	0.3580	0.0603
Preferred	0.3681	0.1025
Non-preferred	0.0908	0.0204

included the deductible for medical services and the co-payment for outpatient visits as our out-of-pocket price measures for medical services.

Table 2 describes the history of prescription drug benefits for the nine firms and the drug price index for the health plans within each employer. Each firm changed its prescription drug benefits at least once, with a total of 18 price changes during the 1997–2003 period. Because of this, there is no "control group" of firms having no drug plan changes over our sample period.

Table 2: Prescription Drug Benefits for Firms in the Study Sample

ID		1997	1998	1999	2000	2001	2002	2003
1	Card plan	4–4	4–8	4–8				
	Mail order	4–4	4–8	4–8				
	Price index	4.00	6.33	6.33				
2	Card plan			12–12	12–12	12–12	12–12	12–16
	Mail order			12–12	12–12	20–20	20–20	20–36
	Price index			12.00	12.00	13.47	13.47	17.27
3	Card plan		5–10	5–15	5–15–25	5–15–25	7–20–40	
	Mail order		6–12	6–18	10–30–40	10–30–40	14–40–70	
	Price index		8.22	11.25	14.08	14.08	19.87	
4	Card plan			5–10–25	5–10–25	5–15–30	5–15–30	5–15–30
	Mail order			10–20–45	10–20–45	10–30–70	10–30–70	10–30–85
	Price index			11.31	11.31	15.60	15.60	15.90
5	Card plan			4–12	8–18	10–20–30	10–25–35	11–27–42
	Mail order			12–36	24–54	20–40–60	20–50–70	22–54–84
	Price index			12.09	19.21	20.20	23.72	26.27
6	Card plan	7–7	9–9–15	9–9–15				
	Mail order	7–7	9–9–15	9–9–15				
	Price index	7.00	9.67	9.67				
7	Card plan	5–10	8–16	8–16	8–16–25	8–16–25	10–20–40	10–20–40
	Mail order	5–10	8–16	8–16	8–16–25	8–16–25	15–30–60	15–30–60
	Price index	7.91	12.66	12.66	13.66	13.66	19.78	19.78
8	Card plan	5–10	5–10	5–10	5–10	6–15	6–15	6–15
	Mail order	8–15	8–15	8–15	8–15	9–25	9–25	9–25
	Price index	8.71	8.71	8.71	8.71	12.65	12.65	12.65
9	Card plan					10–10	10–10	10–20
	Mail order					15–20–30	15–20–30	20–45–60
	Price index					11.74	11.74	19.80

NOTE: The first column indicates the firms' identification numbers. The X–Y and X–Y–Z structures in the 1997–2003 columns represent the card-plan and mail-order dollar amounts of the two-tier and three-tier co-payment schedules, respectively, where X denotes the co-payment for generic drugs; Y denotes the co-payment for branded drugs in a two-tier schedule and the co-payment for preferred branded drugs in a three-tier schedule; and Z denotes the co-payment for non-preferred branded drugs in a three-tier schedule. Price indexes are calculated for each insurance plan based on the co-payments and population weights of each type of prescription.

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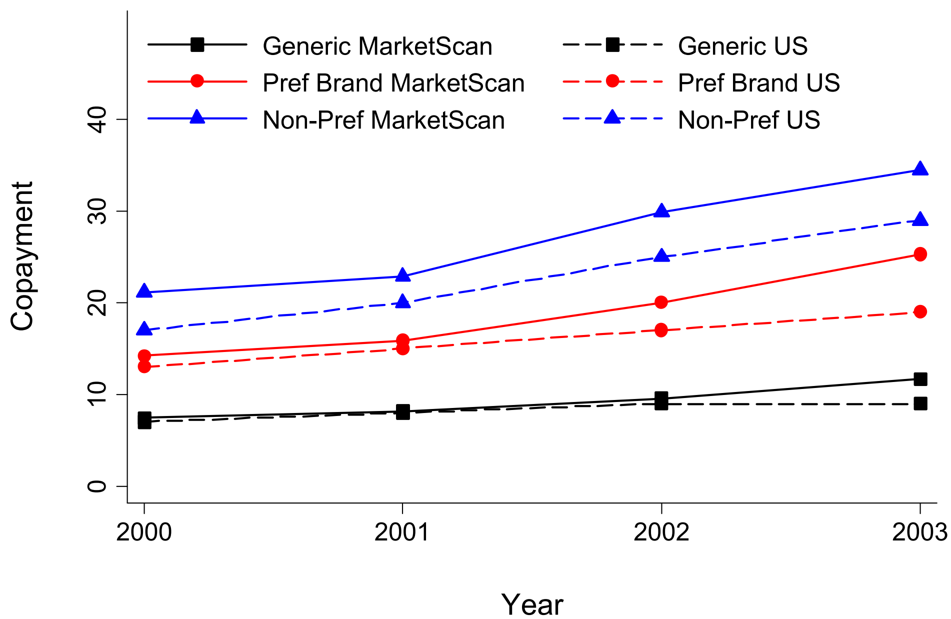
As is clear in Table 2, each benefit change was an increase in co-payments and therefore made prescription drug insurance less generous. This is consistent with the national trend of increasing drug co-payments over the past decade. Figure 7 compares the average co-payments for generic, preferred branded, and non-preferred branded drugs of the nine firms in our study with those of the employer-sponsored prescription drug insurance plans for the U.S. population. The estimates of drug co-payments for the U.S. population are from the Employer Health Benefits Annual Surveys conducted by HRET from 2000 to 2003.[10]

Table 3 gives definitions of all the variables used in the demand estimation, and Table 4 provides summary statistics for these variables. Our dependent variables were the spending and use variables for prescription drugs, outpatient care, and inpatient care. We constructed the total spending variable as the sum of spending on these three types of medical care. In Table 4, we also report the number of observed zeros in the corresponding quantity and spending variables. In our sample, 96% of the person-years saw no inpatient admissions, compared

Figure 7: Co-payment Representativeness



[10] The Employer Health Benefit Annual Survey is funded by the Kaiser Family Foundation and has been studied jointly by HRET and the Kaiser Family Foundation since 1987. It collects health insurance benefits information from approximately 2,000 randomly selected employers in all major industries. For details, see http://www.kff.org/insurance/ehbs-archives.cfm.

Table 3: Variable Descriptions

Variable	Description
RxS	Annual spending on prescription drugs
OUTS	Annual spending on outpatient services
INS	Annual spending on inpatient services
TOTS	Annual total spending
DAYSUPP	Days of drugs supplied
NUMV	Number of outpatient visits
NUMADM	Number of inpatient admissions
RxP	Drug co-payment index
DEDUCT	Deductible for medical services
COPAY	Co-payment for one physician office visit
RETIRE	1 = retired, 0 = still working
AGEGROUP	Age group: 1 = 0–10; 2 = 11–18; 3 = 19–29; 4 = 30–39; 5 = 40–49; 6 = 50–59; 7 = 60–64
AGE1YEAR – AGE7YEAR	Interaction of age group with year

Table 4: Summary Statistics

Variable	Mean	Std Dev	% Zeros	% Always User	% Always Non-User
RxS	624	1756	29.52	52.24	12.94
OUTS	1614	5156	16.72	68.18	6.05
INS	714	6918	95.78	0.42	87.35
TOTS	2951	10242	13.00	74.83	4.45
DAYSUPP	331	584	29.52	52.24	12.94
NUMV	16.61	27.83	16.72	68.18	6.05
NUMADM	0.06	0.33	95.78	0.42	87.35
RxP	15.30	5.32	–	–	–
DEDUCT	134	168	–	–	–
COPAY	6.50	7.06	–	–	–
RETIRE	0.18	–	–	–	–
AGE1TIME	0.71	2.13	–	–	–
AGE2TIME	0.83	2.31	–	–	–
AGE3TIME	0.57	1.96	–	–	–
AGE4TIME	0.98	2.48	–	–	–
AGE5TIME	1.47	2.93	–	–	–
AGE6TIME	1.58	2.98	–	–	–
AGE7TIME	0.71	2.09	–	–	–
1998	0.05	0.22	–	–	–
1999	0.11	0.32	–	–	–
2000	0.19	0.39	–	–	–
2001	0.22	0.41	–	–	–
2002	0.22	0.41	–	–	–
2003	0.17	0.38	–	–	–

N = 1,713,879; No. of individuals = 526,086.

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with 30% for prescription drug use and 17% for outpatient care. Also, 87% of individuals used no inpatient care during the time span for which data were available for them, compared with 13% for prescription drugs and 6% for outpatient care. We describe our empirical strategy for coping with the large number of zero values in the next section.

By construction, there was no switching among an employer's drug plans because our employers all had uniform drug plans over time. But switching among medical plans was still of potential concern. In our data, employers had on average 2.76 medical plans available to their employees. Table 5, which presents insurance plan switching rates for each firm, shows that switching rates were small. One might interpret these low switching rates as indicating that even though people may self-select into insurance plans, their selections seem to be determined mostly by stable health or preference factors at the baseline year. If this is true, the individual FE will largely account for unobservable factors that drive selection.

Table 5: Percentage of People Switching Among Insurance Plans

Firm ID	Plan	1997	1998	1999	2000	2001	2002	2003
1	Medical	—	0	0				
	Drug	—	0	0				
2	Medical			—	0	0.11	1.8	2.18
	Drug			—	0	0	0	0
3	Medical		—	0	2.88	1.11	1.14	
	Drug		—	0	0	0	0	
4	Medical			—	0.13	0.19	0.29	0.97
	Drug			—	0	0	0	0
5	Medical			—	0	7.13	0	0
	Drug			—	0	0	0	0
6	Medical	—	0	0				
	Drug	—	0	0				
7	Medical	—	1.13	0.99	0.92	1.17	0.39	0
	Drug	—	0	0	0	0	0	0
8	Medical	—	0.45	0.34	0.14	0.58	0	0
	Drug	—	0	0	0	0	0	0
9	Medical					—	0	0
	Drug					—	0	0

4. Empirical Strategy

4.1 Model Specification

We estimated equations relating demand for and total spending on prescription drugs, outpatient care, and inpatient care to the out-of-pocket prices paid by consumers for drugs and to the medical plan design characteristics. The basic estimation model is

$$Q_{it}^{j} = \beta_1^j + \beta_2^j P_{it}^d + \beta_3^j P_{i,t-1}^d + \beta_4^j P_{it}^m + \beta_5^j P_{i,t-1}^m + x_{it}\delta_j + \alpha_i^j + \gamma_t^j + \varepsilon_{it}^j \qquad (2)$$

In this equation, Q_{it}^{j} denotes demand for health input *j* by person *i* in period *t*, where *j* indexes prescription drugs, outpatient care, and inpatient care. The variables P_{it}^{d}, P_{it-1}^{d} are, respectively, indexes of the contemporaneous and lagged patient out-of-pocket prices for prescription drugs, and $P_{it}^{\mathrm{m}}, P_{it-1}^{\mathrm{m}}$ stand for prices for other types of medical care, such as outpatient and inpatient care. The x_{it} capture all non-price time-varying variables that also affect demand for medical care, such as retirement status and interactions between age group and year. The error term can be decomposed into three separate elements. The term α_i^j captures unobservable and unchanging individual heterogeneities in medical demand, such as individuals' preferences for using medical goods and inherited traits. The term γ_t^j captures the general trend effects in demand over time, and ε_{it}^j stands for all other random factors that might affect demand.

Since we were concerned with the dynamic effects of out-of-pocket drug prices on both drug demand and demand for other medical services, throughout our analysis we included both the current drug price index and one lag of the drug price index. In this model, the "long-run" effect of a change in out-of-pocket prescription drug prices is the sum of the effects of both the contemporaneous and the lagged price variables. We were unable to use a lag structure longer than one year, since this would have required us to include only those firms having four or more years of usable data, thereby substantially reducing our sample size.[11]

The spending measure we used throughout was the total spending on the relevant service. For example, total spending on drugs is the consumer's out-of-pocket spending plus the insurance plan's spending, subject to the caveats above. It is important to distinguish our regression of total spending on price from the more familiar expenditure function approach to estimating demand. Our total spending regressions are not expenditure function regressions, because the left-

[11] Adding two lags in the regression causes the loss of three of nine firms. The total number of individuals falls to 355,920, from 526,086.

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hand-side spending variable is *not* solely the consumer's total spending, but, instead, the consumer's total spending plus the plan's total spending. Therefore, our price elasticity of spending is *not* the consumer's price elasticity of demand plus one, as it is in consumer theory. The spending variable here is more like a quantity index: it weights each prescription by the *total* (as opposed to the out-of-pocket) price paid for the prescription.

4.2 Econometric Issues

Throughout the analysis, we used FE to control for unobserved individual characteristics. This choice was motivated by several considerations. The consumer-specific information we had access to is quite sparse. For example, we had no income information, and the only health status information was what we could infer from the claims data.[12] Second, although there was little switching among medical plans over time, there was still the prospect of adverse selection: Consumers may already have selected into their health plans at baseline. Thus, we hoped to control for unobserved consumer characteristics and to mitigate adverse selection by including individual FE. Since firms' FE are contained in the span of the individual FE, use of this strategy means we were identifying the effects of the out-of-pocket drug prices solely from the variation induced by changes in the drug plans within a firm over time.

Over our sample, firms changed not only the design of their drug benefits, but also the design of their other medical benefits (co-payments, deductibles, etc.). In addition, a small number of employees switched from one medical plan to another over time. To deal with this, we included controls for the non-drug design characteristics of the health plans in all our regressions. However, if changes in a non-drug health plan design were always or nearly always to accompany changes in a drug plan design, this would be cause for concern. In Table 6, we present a contingency table showing the joint distribution of drug plan design changes and non-drug plan design changes. Of the 34 firm-years[13] in the analysis, 18 featured drug plan design changes and 12 featured non-drug plan design changes. Non-drug benefit changes appear slightly more likely to occur when drug benefits change (43% vs. 31%). However, this relationship is not significant at conventional levels ($p = 0.6$), and the correlation between the two change dummy variables is 0.08.

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[12] We could have attempted to estimate health status from the claims data by using a baseline period. However, that would have required shortening our panel, compromising the estimation of dynamic effects and making it more difficult to control for other aspects of unobserved individual heterogeneity.

[13] There were 43 firm-years of data. Since we were analyzing changes in benefits, however, we had to omit the first year of data for each of the nine firms.

Table 6: Changes in Plan Benefit Design

Drug Plan Change	Medical Plan Change: No	Yes	Total
No	11	5	16
Yes	11	7	18
Total	22	12	34

Pearson's $\chi^2 = 0.22$, $p = 0.6$.

We used linear FE models for both the quantity and expenditure equations. This approach is straightforward, but there were a number of econometric issues associated with the use of linear FE estimators given the nature of some of our data. The measures of quantity were counts, and some of the expenditure variables had significant probability mass at zero. We therefore also employed a FE count data model and a FE Tobit model to estimate the quantity and spending equations, respectively.

Errors in the demand equations for a particular consumer are likely to be serially correlated. We therefore used the block bootstrap method (with blocking at the individual consumer level) to adjust standard errors for serial correlation and heteroskedasticity.

There was a potential for mean reversion to affect our results. If firms change their benefit designs in response to unusually high spending and the spending mean reverts, one could see falling spending following a change in benefit plan design in the absence of a true effect of benefit plan design on spending. In our context, since all changes in drug plan design were toward less generosity, this would likely lead us to overestimate the effect of price on drug demand. Presumably, this effect would also lead us to underestimate the effect of drug price increases on inpatient and outpatient demand, since demand for these services would fall (for mean reversion reasons) after an increase in drug prices.

4.2.1 FE Count Data Model. As Table 3 documents, our quantity variables were counts, and as Table 4 shows, some of them were frequently zero. We thus used FE Poisson count data methods to model them. Specifically, we used Hausman, Hall, and Griliches's (1984) conditional maximum likelihood estimator (HHG). This estimator is based on a conditional mean assumption, $E\left(Q_{it}^{j}\right)=\exp\left(\phi_i^j + X_{it}\theta_j\right)=\exp\left(\phi_i^j\right)\exp\left(X_{it}\theta_j\right)$,where the FE take the multiplicative form $\exp\left(\phi_i^j\right)$. Estimation is straightforward, since the individual FE parameters

ϕ_t^j are conditioned out in the log-likelihood function. HHG has strong robustness properties. Consistency requires only that the conditional mean assumption is correct. Except for the conditional mean, the distribution of y_{it} given $\left(\phi_t^j, x_{it}\right)$ is completely unrestricted. That implies that the estimates are consistent in the presence of overdispersion, underdispersion, or serial correlation (Wooldridge, 1999).

4.2.2 FE Tobit Model. It would have been inappropriate to use linear regression models for the spending variables given the large number of zeros observed for each. Obviously, these zeros arose when consumers did not use any of the services in the relevant category in a year.[14] We therefore used FE Tobit models to estimate the parameters of the spending models.

Although there is a large body of literature on identification and estimation of linear panel data models with FE, FE limited dependent models have not been as fully studied. Honoré (1992) and Honoré and Kyriazidou (2000) propose a semi-parametric estimator for the FE Tobit model. The idea for this estimator is to restore the symmetry of the distribution of the dependent variable that was destroyed by censoring.

Honoré proposes two estimators—the trimmed least absolute deviation (LAD) estimator and the trimmed least square (LS) estimator—for FE Tobit models. These two estimators are essentially generalizations of Powell's (1984) LAD estimator and Powell's (1986) trimmed LS estimator for censored regression. Each estimator is consistent and asymptotically normal under fairly weak assumptions. Moreover, these estimators do not impose parametric structure on the distribution of error terms.

Deaton (1997) points out that Powell's (1984, 1986) censored LAD estimator and censored LS estimator can be calculated easily by the repeated application of the linear least squares or least absolute deviations regression algorithms. This point is further discussed by Chay and Powell (2001). Simply put, these estimators can be achieved by iterating between "symmetric trimming" of the dependent variables using estimates from the previous iteration and least squares or median regression using the "trimmed" data. To derive our FE Tobit estimates, we used the identically censored least squares (ICLS) estimator of Honoré as described by Chay and Powell (2001).

4.2.3 Serial Correlation in Panel Errors. Estimating health care demand using longitudinal data is subject to a potential serial correlation problem. Several studies show that consumers' health spending is persistent from one year to the

[14] The large number of zeros in conjunction with a FE approach also poses problems for the commonly employed "two-part" model of health spending. With fixed effects, any person who either used a service in every year or never used a service is dropped from the first part (the probit for used/not-used) of the two-part model.

next (Eichner, McClellan, and Wise, 1998; van Vliet, 1992; Pauly and Zeng, 2003) and that there is habituation in drug prescribing and use (Coulson and Stuart, 1992; Hellerstein, 1998; Coscelli, 2000). We used the block bootstrap method to correct our standard errors for serial correlation. The block bootstrapping was done at the individual consumer level so that we were correcting for serial correlation and heteroskedasticity at this individual level, and we used 250 replications in all cases. Since we had to drop one year of data because of the lagged prices, our panel data had small T (3.3 on average per person) and large N (526,086), a setting for which Bertrand, Duflo, and Mullainathan (2004) find the bootstrap to be a good choice. The bootstrap has the merit of avoiding strong parametric assumptions about the structure of the error variance matrix. The serial correlation problem and possible solutions to it for nonlinear panel models, such as FE Poisson models and FE Tobit models, which we estimated in this study, are still not fully explored in theory.

5. Results[15]

Figure 8 shows the time series movements of per capita prescription drug spending and average out-of-pocket prices for prescription drugs over the study period, 1997–2003. These drug prices are the weighted averages of yearly pharmaceutical price indexes at the firm level. Over this period, both the average co-payment and the average spending per enrollee increased.[16] Furthermore, the correlation over time between de-trended average co-payment and de-trended average spending is 0.38 (N = 7), and the ordinary least squares (OLS) regression coefficient from a regression of spending on co-payment and a time trend is 48.33.

Table 7 summarizes the estimation results for the spending equations, and Table 8 summarizes the results for the quantity equations. In Table 7, we present results from individual linear FE models and FE Tobit models. In Table 8, we present results from individual linear FE models and FE Poisson models. For each model in Table 7 and Table 8, we present results from both a "static" specification, in which only contemporaneous drug and medical benefit design variables are included, and from a "dynamic" specification, in which both contemporaneous and once lagged drug and medical benefit design variables are included.

[15] The FE Tobit results for the inpatient equation presented here are different from results presented in earlier versions of the paper because we discovered and corrected programming errors in our implementation of the estimators.
[16] The use of median medical spending, median drug spending, and median co-payment results in qualitatively similar graphs.

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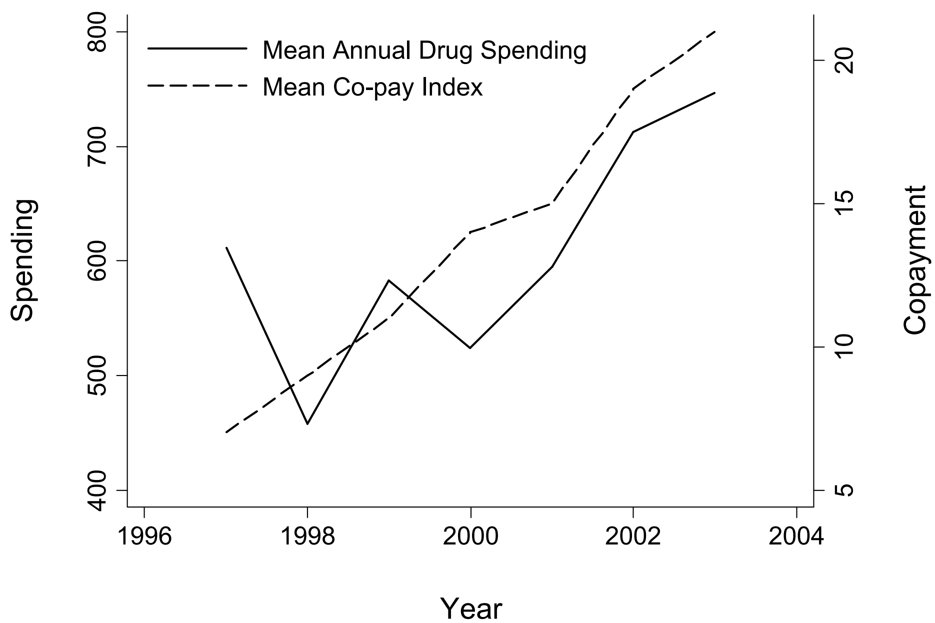
Figure 8: Trends in Co-pay and Spending



In each table, point estimates of average marginal effects are reported. The parameter significance indicators are based on block bootstrapped standard errors that cluster residual errors at the individual level. For each demand variable, only the coefficients of contemporaneous and lagged drug prices are reported. The estimates of the coefficients for the control variables are available online at http://www.heinz.cmu.edu/~mgaynor.

5.1 Effect on Drug Demand

The coefficients for prescription drug demand yield consistent results through all specifications. Increases in out-of-pocket drug prices cause fewer days of drug use and reduce spending on drugs. For example, the individual FE Tobit estimates in the dynamic model suggest that a $1 increase in drug price reduces total drug spending by $23.62 in the first year after the price change and by a further $8.95 in the second year. This corresponds to a "short-run" elasticity of –0.6 and "long-run" elasticity of –0.8 for drug spending. The regression results for days of drug supply follow a similar pattern. The static FE Tobit model shows an estimated own spending price elasticity of –0.5. These results are consistent with previous findings that more-stringent drug cost-sharing benefits are associated with reductions in drug use and drug spending. Based on our calculations,

Table 7: Estimation Results for Spending Equations

	FE OLS				FE TOBIT			
	Static		Dynamic		Static		Dynamic	
	Point Estimate	Elasticity	Point Estimate	Elasticity	Marginal Effect	Elasticity	Marginal Effect	Elasticity
Drug spending								
RxP	–17.29***	–0.42	–20.34***	–0.50	–19.88***	–0.49	–23.62***	–0.58
	(0.66)		(0.80)		(0.59)		(0.75)	
RxP_{t-1}			–13.49***	–0.33			–8.95***	–0.22
			(0.84)				(0.73)	
Outpatient spending								
RxP	9.21***	0.09	10.28***	0.10	3.04*	0.03	6.41***	0.06
	(2.62)		(2.90)		(2.63)		(2.67)	
RxP_{t-1}			12.70***	0.12			9.41***	0.09
			(3.34)				(3.24)	
Inpatient spending								
RxP	–2.76	–0.06	–3.45	–0.07	–2.11	–0.05	–1.44	–0.03
	(4.74)		(4.35)		(2.41)		(2.58)	
RxP_{t-1}			–4.97	–0.11			0.33	0.01
			(5.01)				(3.06)	
Total spending								
RxP	–10.84*	–0.06	–13.51**	–0.07	–21.17***	–0.11	–20.88***	–0.11
	(5.83)		(5.83)		(6.00)		(6.17)	
RxP_{t-1}			–5.76	–0.03			–0.35	0.00
			(6.56)				(6.48)	

NOTE: Standard errors are derived via an individual-level block bootstrap with 250 replications.
*** Statistically significant at 0.001 level ** Statistically significant at 0.05 level * Statistically significant at 0.1 level.

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Table 8: Estimation Results for Quantity Equations

	FE OLS				FE Poisson			
	Static		Dynamic		Static		Dynamic	
	Point Estimate	Elasticity	Point Estimate	Elasticity	Marginal Effect	Elasticity	Marginal Effect	Elasticity
Drug supply days								
RxP	–9.66***	–0.45	–11.47***	–0.53	–12.94***	–0.60	–15.7***	–0.73
	(0.16)		(0.18)		(0.24)		(0.21)	
RxP_{t-1}			–8.60***	–0.40			–10.6***	–0.49
			0.18				(0.21)	
Outpatient visits								
RxP	0.05***	0.05	0.05***	0.05	–0.013	–0.01	–0.026**	–0.02
	(0.02)		(0.01)		(0.02)		(0.01)	
RxP_{t-1}			0.18***	0.17			0.101***	0.09
			(0.01)				(0.02)	
Hospital admission								
RxP	–0.0003*	–0.07	–0.0003	–0.08	–0.002	–0.003†	–0.0026	–0.03†
	(0.0002)		(0.0002)		(0.002)		(0.0015)	
RxP_{t-1}			–0.0005**	–0.13			–0.0043**	–0.05†
			(0.0002)				(0.0016)	

NOTE: Standard errors are derived via an individual-level block bootstrap with 250 replications.
*** Statistically significant at 0.001 level ** Statistically significant at 0.05 level * Statistically significant at 0.1 level.
† These elasticities are calculated using the number of inpatient admissions for inpatient care users.

Joyce et al. (2002) find drug spending elasticities of co-payment of between –0.2 and –0.3, while Balkrishkan et al. (2001) find an elasticity of–1.27.[17]

One distinguishing aspect of our analysis is the examination of dynamic effects on demand. The results from our study show that there are significant and strong lagged price effects on the demand for drugs. These results suggest that there are substantial adjustments to drug consumption in the long term, along with considerable shorter-term stickiness.

5.2 Effect on Outpatient Demand

Results from both the OLS and Tobit estimations suggest that consumers facing higher drug co-payments substitute outpatient services in both the short and the long run. Specifically, the dynamic, individual FE Tobit results in Table 7 indicate that a $1 increase in the out-of-pocket drug price index increases per capita outpatient spending by $6.41 in the first year and $15.82 in the second year after the price change (i.e., there is a *further* increase of $9.41). These estimates correspond to short-run and long-run cross-price elasticities of 0.1 and 0.2, respectively.

The FE Poisson results in Table 8 indicate that a $1 increase in the out-of-pocket drug price index leads to 0.026 fewer outpatient visits in the first year but 0.075 more outpatient visits in the second year after the price change. These correspond to short-run and long-run cross-price elasticities of –0.02 and 0.07 with drugs, respectively. One limitation associated with the measure of the number of outpatient visits is that outpatient visits are not homogeneous. An outpatient surgery counts the same as a physician office visit.

5.3 Effect on Inpatient Demand

The results for inpatient care suggest no measurable relationship between drug prices and inpatient spending and a small relationship between drug prices and inpatient quantity. Observe that no inpatient coefficient in Table 7 is significant, either statistically or economically. In Table 8, lagged drug prices seem to have a small, negative effect on inpatient admissions. Our findings on inpatient substitution are in sharp contrast to those in Goldman, Joyce, and Karaca-Mandic (2006). Those authors found that higher co-payments for cholesterol-lowering drugs are associated with significantly fewer admissions among patients who have started cholesterol-lowering drug therapy.

5.4 Effect on Overall Spending

Increases in out-of-pocket drug prices have a smaller effect on overall spending than on drug spending. A $1 increase in the out-of-pocket drug price reduces total spending by $20.88 in the first year and a further $0.35 in the second year, with

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[17] Other papers in the literature did not have easily computable elasticities.

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only the contemporaneous effect achieving statistical significance. Thus, the long-run drop in total spending, \$21.23, is about 65% of the long-run drop in drug spending, \$32.57.

It is worth noting that the OLS results are very similar. A \$1 increase in the drug co-payment reduces drug spending by \$20.34 in the first year and \$33.83 in the second, while total spending falls by \$13.51 in the first year and \$19.27 in the second. The long-run total expenditure savings is therefore about 60% of the long-run drug expenditure savings.

5.5 Subgroup Analysis: Chronic Conditions

In Tables 9 and 10, we present an analysis that separates individuals according to whether they have a chronic condition. Specifically, we identify all individuals who have a diagnosis code indicating hypertension, high cholesterol, or asthma as chronically ill. Table 9 shows descriptive statistics stratified by chronic illness status; as one would expect, chronically ill people are older and spend more on health care. In Table 10, we present the results of separate FE regressions stratified according to chronic illness status. In each category, the qualitative

Table 9: Summary Statistics, Stratified by Health

	Without Chronic Condition		With Chronic Condition	
	Mean	**Std Dev**	**Mean**	**Std Dev**
RxS	385	1514	1291	2445
OUTS	1246	4026	2936	7732
INS	370	4606	1614	11284
TOTS	2000	7268	5841	16115
DAYSUPP	180	374	745	846
NUMV	13	23	29	39
NUMADM	0.04	0.24	0.12	0.49
RxP	13.86	3.76	13.50	3.84
RxP_{t-1}	12.06	3.19	11.73	3.26
DEDUCT	54.86	76.44	68.37	77.11
$DEDUCT_{t-1}$	54.81	74.14	68.66	75.31
COPAY	8.35	6.92	7.17	6.84
$COPAY_{t-1}$	7.05	5.66	5.98	5.58
RETIRE	0.15	0.35	0.34	0.47
AGE	33.73	18.12	48.16	15.14
No. of observations:	1,280,086		465,426	

Table 10: Linear FE Regression Results for Spending, Stratified by Health

	Without Chronic Condition				**With Chronic Condition**			
	Linear FE		**Tobit FE**		**Linear FE**		**Tobit FE**	
	Point Estimate	**Std Dev**	**Marginal Effect**	**Std Dev**	**Point Estimate**	**Std Dev**	**Marginal Effect**	**Std Dev**
Drug spending								
RxP	–8.14	0.65	–12.16	0.56	–49.31	1.69	–42.21	1.21
RxP_{t-1}	–5.08	0.71	–4.94	0.68	–27.26	1.76	–14.10	1.46
Outpatient spending								
RxP	8.57	2.18	2.56	2.35	13.20	7.54	16.39	6.22
RxP_{t-1}	13.78	2.38	9.85	2.84	10.47	7.87	10.69	7.42
Inpatient spending								
RxP	–1.09	2.34	–1.44	1.96	–11.39	13.61	–1.18	3.02
RxP_{t-1}	0.23	2.56	1.66	2.43	–19.87	14.20	–1.77	3.76
Total spending								
RxP	–0.66	3.62	–12.34	4.61	–47.50	17.02	–38.08	15.38
RxP_{t-1}	8.92	3.95	7.45	5.60	–36.67	17.76	–15.13	18.38
No. of observations	1,280,086				465,426			

NOTE: Standard errors are derived via an individual-level block bootstrap with 50 replications.

results are the same. Increasing drug out-of-pocket payments lowers drug spending and lowers total spending. The absolute magnitude of the effects is larger for the chronically ill group.

The decrease in total spending is lower than the decrease in drug spending in each group. For the chronically ill group, the long-run reduction in drug expenditures is $56.31, and the long-run reduction in total expenditures is $53.23 (95% of the long-run drop in drug expenditures). For the non-chronically ill, the long-run reduction in drug expenditures is $17.10, and the long-run drop in total expenditures is $4.89 (only 29% of the drop in drug expenditures). In addition, the substitution toward outpatient care seems to be larger in absolute magnitude but similar in percentage terms among the chronically ill.

5.6 Generic Substitution

Esposito (2005) found that relative out-of-pocket price differences influence consumer choice of drug within class. We carried out a brief exploration of whether tiering had an effect on generic/branded choice. We calculated a generic and a branded price index for each firm-year by re-weighting the index weights in Table 1 separately for generics and branded drugs. For example, a firm's generic price index was equal to 0.85 (= 0.358/[0.358+0.06]) times its generic card-plan co-payment plus 0.15 times its generic mail-order co-payment. The employee-weighted average of the ratio of generic to branded price indexes was 0.63 in 1997 and drifted down to 0.44 in 2003. Over the same time, the employee-weighted average of firm-year ratios of generic to branded prescriptions rose from 0.64 to 0.77. In a year and firm FE regression, the generic/branded price ratio had no measurable impact on the generic/branded prescription ratio (coefficient of –0.01, standard error of 0.09). So, in our sample, there does not appear to be strong evidence of substitution between generic and branded drugs, although the effect is in the "right" direction.

6. Summary and Conclusions

We estimated consumers' responses to pharmaceutical cost sharing, accounting for the contemporaneous and lagged responses of drug, outpatient, and inpatient quantity and spending to increases in drug co-payments. Our results show that increased consumer cost sharing for prescription drugs reduces both use of and spending on prescription drugs. We also found dynamic adjustment by consumers: The effects one year after a co-payment increase were substantially larger than the contemporaneous effects. Moreover, consumers substitute outpatient care in response to rising drug prices, and this effect also has a significant dynamic component: There was substantially more substitution of outpatient care one year after an increase in pharmaceutical cost sharing. There was little measurable substitution between drugs and inpatient care.

In total, we found that the expenditure savings on prescription drugs are substantially offset by increases in outpatient spending. A $1 increase in drug price reduced drug spending by $23.62 in the first year after the price change and by $32.57 in the second. Total spending fell by $20.88 in the first year and $21.23 in the second. Thus, in the long run, total spending fell by about 65% as much as drug spending did—i.e., 35% of the savings achieved by reductions in drug spending were offset by consequent increases in other medical spending. Higher drug co-payments save money on drug spending, but they cost money on outpatient and possibly inpatient spending and have smaller effects on overall spending. Our findings suggest that high consumer cost sharing may not be as effective a mechanism for controlling spending as previously thought.

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