Is drug coverage a free lunch?: Cross-price elasticities and the design of prescription drug benefits

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Abstract

Recently, many US employers have adopted more stringent prescription drug benefits. In addition, the U.S. will offer prescription drug insurance to approximately 42 million Medicare beneficiaries in 2006. We use data from Medstat on individual claims and benefit design from 1997-2001 to examine the dynamic structure of demand for health care, focusing specifically on whether prescription drugs are (dynamic) complements or substitutes for inpatient and outpatient care. We study the effect of changing consumers' copayments for prescription drugs on the quantity demanded of and expenditure on prescription drugs, inpatient care and outpatient care, allowing for effects both in the year of the copayment change and in the year following the change. Our results show that a one dollar increase in the consumer copayment for drugs has the following effects: in the first year after the change, drug spending, outpatient spending, inpatient spending, and total spending fall by $9.71, $6.46, $3.39, and $20.39, respectively. In the second year after the change, drug spending falls by $8.35, while inpatient spending, outpatient spending, and overall spending rise by $10.71, $13.03, and $22.85, respectively. Raising consumer drug copayment by $1 per prescription actually **raises** overall spending by about $1 per enrollee per year over two years (ignoring discounting). This implies that more generous prescription drug benefits may be costly in the short run, but can generate cost savings in the long run. These long run effects should be taken into account when estimating the expected cost of programs like the Medicare prescription drug benefit.

I. Introduction

Spending on outpatient prescription drugs has increased at double digit rates in the 90s and early this decade. In the private sector the drug spending rose at 15-20 percent per year during this period[1]. Moreover, these increases are projected to continue at 10.7 percent rate annually between 2004 and 2013[2]. Prescription drug spending has become the third largest component of health care expenses after hospital care and physician services, and now account for more than 11% of total health care spending. In an effort to contain drastically rising drug costs, employer-sponsored plans began to adopt more stringent prescription drug benefits by increasing drug copayments and establishing tiered cost-sharing formulas. As a result the prices patients pay out of pocket for prescription drugs have been increasing substantially in recent years. For example according to statistics from Kaiser Family Foundation, the average copayments for generic drugs increase from $7 in 2000 per prescription to $9 in 2003. Copayment for preferred drugs (those included on a formulary or preferred drug list, such as a brand name drug with a generic substitute) increased by 62%, from $13 per prescription in 2000 to $21 in 2004. During the same time period, copayment for non-preferred drugs (those not included on a formulary or preferred drug list) have increased 94%, from an average of $17 per prescription in 2000 to $33 in 2004.

There have been extensive studies focusing on the impacts of the changes in prescription drug benefits on the use and costs of prescription drugs, and the resulted health status. Some studies showed that the increased drug cost-sharing reduced pharmaceutical use and/or costs (Joyce [2002], Huskamp [2003], Soumerai [1987, 1991], Harris [1990], Johnson [1997], Tamblyn [2001], Motheral [2001], Goldman [2004]). For example, Joyce et al. found that doubling the copayment for each prescription reduced drug costs by 19%-33%. Goldman et al. (2004) concluded that increase cost-sharing in drug benefits are associated with reduction in

[1] Kaiser Family Foundation: Prescription drug trends, Oct 2004.
[2] Kaiser Family Foundation and Health Research and Educational Trust, Employer Health Benefits: 2004 Annual Survey, Sept 2004.

use of almost all therapeutic classes of prescription drugs. Moreover, it reduced the use of "nonessential" drugs more than "essential" drugs. The changes in drug benefits also raise the concerns about adverse health consequences, especially for people with chronic illness. The results about whether or not the increases in drug prices are associated with significant adverse health status are unclear. Some studies found that raising drug prices are associated with increased adverse health events (Tamblyn et al. [2001], Johnson et al. [1997], Heisler [2004]), while some other studies reported no significant changes in health status following increased cost-sharing for prescription drugs (Pilote et al.[2002], Schneeweiss et al.[2002]).

These above results seem to justify the cost-containment attempts of the insurers in recent years, at least from the cost perspective. Raising the cost-sharing on prescription drugs reduces moral hazard of excess utilization, without obvious evidence of reduction in health status. However, are these savings in prescription drug expenditures really a free lunch? To answer this question we need to address at least two other questions.

- How does prescription drug consumption relate to the consumption of other medical services, such as inpatient and outpatient care? Are they complements or substitutes?
- All of the early evaluation studies mentioned above focused on examining the instantaneous demand response to changes in drug prices. However, is there any long-term effect of those price changes on consumer's demand for health care, and if so, how is it distributed over a longer time period?

For the first question, the substitute-complement relationship between prescription drugs and outpatient, inpatient cares is not obvious. On one side, patients must see doctors to get prescriptions, and inpatient hospital admissions usually result in follow-up treatments that require the use of drugs. These facts suggest a possible complementary relationship between prescription drugs and outpatient or inpatient care. On the other side, prescription drugs may prevent or reduce future illness and complications, which could reduce future demands for outpatient and inpatient care. Moreover, some diseases can be treated either by taking medication or on the outpatient or inpatient basis. In such cases prescription drugs may be substitutes for outpatient or inpatient care. In sum, the overall substitute-complement relationship between the demand for prescription drugs and other medical services is not clear. The issue of substitutability among different types of medical services has long been of interest to health economists and health practitioners. Most of the existing literature focuses on studying the substitutions between outpatient and inpatient care, but the conclusions from those studies are not consistent. Empirical results of some studies suggest that hospital and ambulatory care are not substitutes, and may in fact be complements (Freiberg and Scutchfield [1976]; Lewis and Keairnes [1970], Doepinghaus [1990]). However, results from some other studies suggest the opposite conclusion (Davis and Russell [1972], Helms et al [1978]). The relationship between demand for prescription drugs and other medical services, however, has not been explored prior to our study. The closest study to date is Lichtenberg's 1996 work. He looked at the effect of changes in the quantity and type of drugs prescribed by physicians on the changes in the utilization of other medical inputs such as hospitalization and surgical procedures, and changes in mortality. Lichtenberg found that the number of hospital stays, bed-days and surgical procedures declined most rapidly for the diagnoses with the greatest change in the total number of drugs prescribed. Based on his estimates an increase of 100 prescriptions is associated with 1.48 fewer hospital admissions, 3.36 fewer inpatient surgical procedures and 83 fewer deaths. The results of Lichtenberg's work suggest the existence of a "substitution" relationship among prescription drugs and other medical inputs in treating certain diseases. However, there is a clear distinction between the "substitution" which Lichtenberg estimated, and the "substitution" we want to explore in this paper. Lichtenberg's empirical results can be best interpreted as the "biological" or "technological" substitution relationship between drugs and other medical inputs in health production. Instead, we are interested in examining the substitution of different medical inputs in consumption. Although these two substitution concepts are closely related to each other, as will be shown in the theoretical model, they are not identical.

To answer the second question we need to examine both the instantaneous and dynamic effects of changes in drug prices. Most previous empirical studies estimated the static effect of drug insurance on demand by restricting the price effects within a one-year period. (Joyce[2002], Huskamp[2003], Goldman[2004]) However, this restriction is too strong an assumption. It will not only be more interesting, but also more appropriate to examine both the short-run price effect and the dynamic price effect from a longer period of time. In fact a theoretical model of health demand dynamics was well established in Grossman's health capital model (1972). In this model health is viewed as a form of human capital. Individuals inherit an initial stock of health that depreciates over time, and can increase the health stock by investment. Investments in health capital are produced by medical goods and consumers' own time. In this dynamic programming framework, the demand for medical care depends not only on the contemporaneous prices, by also on prices from previous periods. Therefore the effects of price changes on the demand for medical care are dynamic and own and cross-price elasticities may differ in the short-run and long-run. Using the demand for prescription drugs as an example, consumers will reduce the consumption of prescription drugs instantaneously in response to rising drug prices. Moreover, patients must see a doctor in order to get prescriptions or refills in the short run. As a result the consumption of outpatient care is also likely to drop in the short-run. However, the resulting under-utilization of prescription drugs and other medical care in the current period may deteriorate health stock in following periods, which might cause long term disease complications that have to be treated in hospital or on an outpatient basis.

In this study we are interested in using consumer behavior theories to examine the dynamic structure of health care demand, focusing specifically on whether prescription drugs are (dynamic) complements or substitutes for inpatient and outpatient care. We study the effect of changing consumers' copayments for prescription drugs on the quantity demanded of and expenditure on prescription drugs, inpatient care and outpatient care in the year of the copayment change and in the year following the change. We think this paper is valuable from at least two perspectives. First, this paper fills a large void in the health economics literature and insurance policy studies. It is the first effort to investigate the comprehensive effects of the recent innovations in prescription drug benefit design. This work provides some insights to the understanding of the overall costs and health consequences resulting from those insurance benefit changes. These results can be informative for the assessment of existing prescription drug insurances for elderly people and the design of Medicare prescription drug benefits, which will be launched in 2006. Second, the longitudinal and individual level Medstat data used for this study give us a chance to explicitly control for the individual heterogeneity in demands for medical care and adverse selection in insurance plans, which are in general not possible for most existing papers using either cross-sectional data or aggregated data.

The rest of this paper is organized as followes: in section II we develop a two-stage budgeting theory model for consumer's consumption choice over medical goods. Section III describes the MarketScan database used for estimation. Empirical implementation and development of this theory model is given in section IV. Section V reports estimation results and section VI concludes.

II. Analytical Model

We model demand for prescription drugs, outpatient and inpatient services as a two-stage budgeting problem. A household is both the demander and producer of health. He obtains utility from the consumption of good health H and non-health goods X. Health H has to be produced by health inputs such as medical services, life styles, genetic traits, etc. The consumer's consumption of H and X goods is restricted by two constraints: 1) the total cost of purchasing non-health good X and health inputs can't exceed the available income Y; 2) the outcome H is constrained by the production technology. The consumer maximizes his utility by optimizing his consumption over (X, H) subject to these two constraints.

Assume a household's preference over the consumption of health H, and other good X, can be characterized by a quasi-concave utility function $U_i = U(X_i, H_i, \varepsilon_1^i)$.

Where ε_1 denotes the individual specific preference over the choice of X and H.

$$\frac{\partial U}{\partial X} > 0, \frac{\partial U}{\partial H} > 0, \frac{\partial^2 U}{\partial X^2} < 0, \frac{\partial^2 U}{\partial H^2} < 0$$

The consumer must produce the health good H by using health inputs such as outpatient care, inpatient care and prescription drug, which are purchased from the market. We assume that the health inputs don't augment the household's utility other than through their capability of producing H. This assumption implies there's no joint production. The health production technology can be described by a production function:

$$H_i = \psi(h_1^i, h_2^i, h_3^i, \varepsilon_2^i)$$

Where h_j denotes the health input j, and j =1, 2, 3 represents prescription drugs, outpatient care and inpatient care, respectively. ε_2 denotes unobservable individual specific health endowments and/or other health factors, such as good or bad life styles which either have direct effect on health, or affect the marginal productivity of health inputs . Assume the health production is quasi-concave. The production set defined by this production function is convex.

In the first stage of the two-stage budgeting problem, the consumer is acting as a firm that produces output H from a vector of medical inputs. At this stage the household's problem is:

Min $C = \sum_i p_i h_i$

s.t. $H = \psi(h_1, h_2, h_3, \varepsilon_2)$.

From the FOC we can derive factor demands as function of factor price vector p, and output H:

$$h_i = \frac{\partial C}{\partial p_i} = h^i(p, H, \varepsilon_2) \qquad (1)$$

The derived cost function is $C = \sum_i p_i h_i = \sum_i p_i h^i(p, H, \varepsilon_2) = C(p, H, \varepsilon_2)$.

At the second stage, the household maximizes his utility by consuming X and H subject to the budget constraint:

Max $U(X, H, \varepsilon_1)$

s.t. $Y = C(p, H, \varepsilon_2) + X$

where Y stands for the household's full income. The price of non-health goods X is normalized to be 1. The FOC of this maximization problem gives the following condition:

$$\frac{\partial U(X, H, \varepsilon_1)/\partial H}{\partial U(X, H, \varepsilon_1)/\partial X} = \partial C(p, H, \varepsilon_2)/\partial H \qquad (2)$$

This equation basically says that the household will allocate his resource in such a way that the relative marginal utility from consuming H and X will equal their relative marginal costs. Solving the above equation we can get the optimal demand for H as:

$$H = H(p, Y, \varepsilon_1, \varepsilon_2) \qquad (3)$$

Substituting (3) into (1), we get the solution to the two-stage budgeting problem. The reduced form of health factor demand functions is:

$$h_i = \frac{\partial C}{\partial p_i} = h^i(p, H, \varepsilon_2) = h^i(p, H(p, Y, \varepsilon_1, \varepsilon_2), \varepsilon_2) = g^i(p, Y, \varepsilon_1, \varepsilon_2) \tag{4}$$

Note that these fact demands are functions of household's full income, the price vector of health inputs, the underlying production technology, preference over X and H, and some random factors. The substitute-complement relationship in consumption of health inputs can be examined by the cross price derivatives:

$$\frac{\partial h^i}{\partial p_j} = \frac{\partial h^i(p, H(p, Y, \varepsilon_1, \varepsilon_2), \varepsilon_2)}{\partial p_j} = \frac{\partial h^i}{\partial p_j}\Big|_{H=\bar{H}} + \frac{\partial h^i}{\partial H} \cdot \frac{\partial H(p, Y, \varepsilon_1, \varepsilon_2)}{\partial p_j} \tag{5}$$

In equation (5) the derivative on the left hand side represents the demand response of health i with respect to the price change of input j. This derivative measures the own price demand response if $i = j$, and the substitution effect of health input i for input j if $i \neq j$. The right hand side of equation (5) shows that the substitution of demand for factor i for factor j can be decomposed into two components: 1) the change in demand due to substitution in production technology when output H is held constant, which is $\frac{\partial h^i}{\partial p_j}\big|_{H=\bar{H}}$, and 2) the demand change due to the change in relative marginal cost of producing H over X given budget constraint Y, $\frac{\partial h^i}{\partial H} \cdot \frac{\partial H(p, Y, \varepsilon_1, \varepsilon_2)}{\partial p_j}$.

Note about the distinction between the "substitution in technology" and "substitution in consumption" in equation (5). It is the "substitution in consumption" that we are interested in examining in this paper. Equation (5) says that in general the size of substitution in consumption will not equal the substitution effect in production. As proven in Appendix A, the size of substitution in consumption is smaller than the substitution in production in response to the change of factor prices.

III. Data

1. The Medstat MarketScan Database

The data used for this study is Medstat's MarketScan database. MarketScan is the largest multi-source private sector healthcare database in the U.S, containing paid claims of more than 7 million privately insured individuals, and over $13 billion in annual healthcare expenditures. It collected data for privately insured employees and their dependents from about 100 large employers, health plans, government and public organizations. This database tracks the individual and family enrollment, utilizations of inpatient care, outpatient care and prescription drugs, health expenditure, and detailed health insurance coverage information from 1990 to 2001.

For the analysis of this study, we linked information from five different files in the MarketScan database in 1997-2001. The first file was the MarketScan enrollment file, which provides patients' demographics and detailed information of their health plan enrollment history. The second file was the Employer Benefit Plan Design file, which provides summary benefit descriptions for major medical and prescription drugs benefits for some health plans in the MarketScan database. The other three files are the MarketScan Hospital Inpatient Claims File, Outpatient Service Claims File, and Outpatient Pharmaceutical Claims File. These are the claims data containing information about patients' medical conditions, diagnosis, utilizations and expenditures on inpatient care, outpatient care and prescription drugs, respectively.

Sample Selection Several sample selection strategies were applied to select eligible health plans and their enrollees for the estimation.. First, an insurance plan must have complete information from all of the five files mentioned above for at least two years to be included in our sample. Some health plans didn't submit prescription drug claims data in some or all of the years during 1997-2001. For example, in 1997 only 18 out of 92 employers (an employer may have one or multiple health plans in a specific year) submitted prescription drug claims data; in 1998, only 17 out of 95 employers actually submitted drug data. The lack of prescription drug claims data cuts down the eligible insurance plans significantly. Moreover, even if the prescription drug claims data were available for some health plans, the insurance information in the Benefit Design Data File for them weren't complete; several key insurance variables such as copayment for prescription drugs, deductible, etc, were missing. These plans were further excluded from our sample.

Second, in estimating the demands for medical services, an inevitable problem is the endogenous health insurance. Within the same firm, sicker people tend to pay higher premiums and self select into insurance plans with more generous coverage. Failing to control for the adverse selection will surely cause biased estimators for the insurance variables. We tried to minimize the impact of selectivity bias by further restricting our choice of plans. In the MarketScan database, a typical employer would offer 2 to 3 insurance plans of different level of generosity. If adverse selections exist, we should expect to observe people switching among plans from one year to the next. Our strategy was to select only the plans where there was few enrollees switching health plans from year to the next. By examining the data we found out that for some "non-switching" firms, different health plans were offered in different geographical locations of the same employer, meaning that employees from such firms had only one insurance option at their working location. Another possible explanation for the "non-switching" is that the insurance plans may be mandantorily assigned, or heavily regulated in those firms. Using these health plans, the selectivity bias in health demands was greatly mitigated. We end up with 9 large employers in our data with 61 distinct health plans in the period of 1997-2001.

Third, after we finalized the selection of 61 health plans, we further cleansed the data within those health plans. An individual had to be continuously enrolled for a full year in 1997-2001 in order to be included as an observation in our sample. Moreover, since we were interested in studying the dynamic price effects on demands, each individual must have had at least two records in our data. This means each individual must have been enrolled for at least two full years during 1997-2001. These selection criteria further ruled out a large portion of enrollees from our sample. Last, people age older than 65 are excluded because those people are covered by Medicare program. We end up with a panel data set of 847,801 observations for 331,689 persons, spanning a five-year period from 1997 to 2001.

Demand Variables Demand for health inputs was measured by both the utilization quantity and expenditure on each type of service. For prescription drugs, the sum of supply days of all prescriptions from a particular year for a patient (DAYSUPP) was used as the measure of quantity demand of that person. Similarly, we defined the quantity demand for outpatient services by the total number of outpatient visits (NUMV), and the quantity demand for inpatient services by the total number of inpatient admissions. (Note that, due to the heterogeneity of each medical goods, the three quantity variables are very rough measures of both the rate and amount of utilization. For example, in the way we define the outpatient quantity variable, a physician office visit, an emergency room admission, or a laboratory test, are all treated equally as one unit of service.)

Another way to measure the demand for health inputs is to use the total expenditure on each type of health service. The total spending on prescription drugs, outpatient services and inpatient services (RXS, OUTS, INS) are calculated as the yearly spending per enrollee.

Socio-demographic Variables Since we use the fixed effect model in our estimation, only the time-varying socio-demographic variables are used. The effect of time constant variables such as race, gender, education, etc are absorbed in the individual fixed effect. The variables we used are marital status (MARRIED), residence location (URBAN), retirement status (RETIRE), and a set of year dummies. We also include a set of interaction of AGEGROUP[3] with the continuous time variable: (AGE1YEAR-AGE7YEAR). The reason we used these interaction variables is to permit spending to grow at different rates for people in different age groups.

Price Variables The primary variables in this study are prices for prescription drugs. In the presence of health insurance, the effective prices of health services are the cost-sharing prices consumers have to pay out of pocket. The most common cost-sharing schedule for prescription drugs is the fixed amount copayment. Very early health plans imposed universal copayment on the use of both generic and brand drugs. However, in recent years more cost-sharing schedules have been developed and adopted by insurance companies in an effort to contain fast growing drug costs. Plans placed drugs into different tiers and imposed different copayment requirements on the drugs in different tiers. In the mid-1990's the most common schedule is the 2-tier copayment schedule. In a 2-tier copayment schedule, patients pay lower (say, $5) for a generic drug, and higher (say, $10) for branded drugs. Later in that decade a less generous 3-tier schedule was implemented. In the 3-tier schedule branded drugs are further differentiated into "preferred" and "non-preferred" within a given therapeutic class, and even higher copayment was imposed on "non-preferred" brand drugs.

Ideally, we would like to calculate the price of prescription drugs as the weighted average of the out-of-pocket copayments for generic, preferred brand and non-preferred brand drugs for each plan. However, in the MarketScan data we can only tell whether a prescription is "generic" or "branded", and there's no way to further differentiate whether the brand drugs are preferred or not. Consequently we've constructed the drug price variable as the weighted average of copayments for generic and brand drugs. The price P^d is calculated by:

$$P_j^D = \bar{P}_{jG} * W_G + \bar{P}_{jB} * W_B ,$$

[3] To approximate the nonlinearity of age effect, age is divided into 7 groups: 0-10, 11-18, 19-29, 30-39, 40-49, 50-59, 60-64.

where P_j^D is the out-of-pocket drug price for insurance plan j; $\bar{P}_{jG}, \bar{P}_{jB}$ are plan $j's$ average copayment for one prescription of generic drugs and brand drugs, respectively; W_G, W_B are the weights for generic or brand prescriptions derived from the whole population.

It is more difficult to come up with a single measure for price of outpatient and inpatient services than the prescription drugs. Insurance benefits for outpatient and inpatient services are more complicated than prescription drugs. Common devices of cost-sharing for medical services usually take the form of a combination of fixed amount deductible, percentage coinsurance for the cost above the deductible, a fixed amount of copayment for one physician office visit, and a stop-loss limit beyond which patients don't pay anymore. The price schedules for these medical services are therefore very complicated and highly nonlinear. It is difficult to construct a single price measure for these services that would correctly reflect the true out of pocket prices consumer pay. Since the price variables for outpatient and inpatient cares are the control variables in our estimation models and are of less importance, we didn't try to construct price variables for them as we did for prescription drugs. Instead we included the insurance variables: deductible (DEDUCT), copayment for outpatient visits (COPAY) and the maximum out-of-pocket payment limit (MAXOOP) in our estimation model to control the effects of these variables on health demands.

Note that the coinsurance rate – a major insurance variable – is not included in the variable list. For the nine employers in our sample, the coinsurance rates for their health plans remained unchanged cross years. This is a coincidence of our unique sample, and might not be true for other plans not included in our sample. In the fixed effect framework which we used to estimate the demand for medical care, the effect of coinsurance will not be able to be estimated and therefore it was dropped from our estimation model.

Moreover, the price indices for outpatient and inpatient services are not included in the estimation models either. Omitting the price index variables from the demand model will cause problems if price growth rates vary geographically or cross plans. We experimented with models including outpatient and inpatient price indices calculated at MSA level. However, including the price index variables is also problematic because those variables are endogenous. One possible approach is to instrument these price variables. We experimented with the Geographical Practice Cost Index (GPCI) developed by Medicare as the instrument for outpatient price index, and the hospital wage index as the instrument for inpatient price index. It turned out these instruments are just weakly correlated with out price indices and standard errors from using these instruments are not usable. Including or excluding these price index variables do not change the parameter estimates significantly for the primary drug price variables and most of other covariates. Therefore, we dropped the price indices from the estimation.

Table 1 provides a description of the prescription drug benefits history for the 9 employers, and constructed drug prices for a typical health plan within each employer. Table 2 gives detailed description of all the variables used in the demand estimation, and Table 3 provides summary statistics of these variables. In Table 3 we also reported the number of observed zeroes in the corresponding quantity and spending variables.

Table1: Prescription Drug Benefits for the 9 Employers

	1997		1998		1999		2000		2001	
	Rx Copay	AveCopay	Rx Copay	AveCopay	Rx Copay	AveCopay	Rx Copay	AveCopay	Rx Copay	AveCopay
FIRM1	C: $4-$8	$6.44	C: $4-$8	$6.60	C: $4-$8	$6.54				
FIRM2	C: $2-$5	$2.33	C: $2-$5	$2.33	C: $2-$5	$2.29				
FIRM3					C:$12-$12-24	$15.26	C: $12-$12-24	$15.06	C:$12-$12-$24 M:$20-$20	$18.40
FIRM4			C: $5-$10 M: $6-$12	$8.45	C: $5-$15 M: $6-$18	$11.70	C: $5-$15-$25 M: $10-$30-$40	$14.07		
FIRM5					C: $5-$10-$25 M: $10-$20-$45	$10.26	C: $5-$10-$25 M: $10-$20-$45	$10.58	C: $5-$15-$30 M: $10-$30-$70	$14.68
FIRM6	C:$7-$7	$7.00	C:$9-$9-$15	$9.50	C:$9-$9-$15	$9.28				
FIRM7	C:$5-$10	$8.22	C:$8-$16	$13.36	C:$8-$16	$13.21	C:$8-$16-$25	$14.17	C:$8-$16-$25	$14.33
FIRM8	C: $5-$10 M: $8-$15	$7.77	C: $5-$10 M: $8-$15	$8.96	C: $5-$10 M: $8-$15	$8.84	C: $5-$10 M: $8-$15	$8.89	C: $6-$15 M: $9-$25	$10.61
FIRM9					C: $3-$5	$4.35	C: $3-$5	$4.32	C: $3-$5-$10	$7.44

Note: C represents Card Plan, and M represents Mail-order Plan.
The $X-$Y or $X-$Y-$Z structures represent the 2-tier and 3-tier Copayment schedules, respectively,
where $X denotes copayment for generic drugs; $Y denotes copayment for brand drugs in a 2-tier schedule, and the copayment for preferred brand drugs in a 3-tier schedule; $Z denotes copayment for non-preferred brand drugs in a 3-tier schedule.

Table2: Descriptions of variables

Variable	Description
RXS	Annual spending on prescription drugs
OUTS	Annual spending on outpatient services
INS	Annual spending on inpatient services
DAYSUPP	Prescription drugs demanded (in days)
NUMV	Number of outpatient visits
NUMADM	Number of inpatient admissions
RXP	Out of pocket prices for prescription drugs
DEDUCT	Deductible for medical services (for outpatient and inpatient)
COPAY	Copayment for one physician office visit
MAXOOP	Stoploss limit for outpatient and inpatient services
AGE1YEAR-AGE7YEAR	The interaction of age group with Year
RETIRE	1 = yes, 0 = no
URBAN	Residence place of employees, 1 = Urban, 0 = Rural
MARRIED	1 = yes, 0 = no
YEAR97-YEAR01	Dummy variables for year of data. Year97=1 if year=1997, etc.

Table3: Summary Statistics of Variables

Variable Name	Mean	Std	# of Zeroes	% of Zeroes
RXS	528	1506	276171	32. 57
OUTS	1539	4689	149687	14. 66
INS	664	7000	809684	95. 46
TOTS	2730	9838	116870	13. 79
DAYSUPP	302	571	276171	32. 57
NUMV	15.94	26.28	149687	14. 66
NUMADM	0.06	0.32	809684	95. 46
RXP	12.61	3.22	-	-
DEDUCT	102	155	-	-
COPAY	5.39	5.31	-	-
MAXOOP	1519	653	-	-
URBAN	0.90	0.29	-	-
MARRIED	0.55	0.50	-	-
AGE1TIME	0.40	1.18	-	-
AGE2TIME	0.45	1.27	-	-
AGE3TIME	0.26	0.98	-	-
AGE4TIME	0.48	1.29	-	-
AGE5TIME	0.73	1.54	-	-
AGE6TIME	0.82	1.59	-	-

YEAR01	0.24	0.43	-	-
YEAR00	0.33	0.47	-	-
YEAR99	0.25	0.43	-	-
YEAR98	0.18	0.38	-	-
# of Observations		847801		
# of Individuals		331689		

IV. Empirical Implementation of the Model

1. The Health Input Demand Functions and the Basic Fixed Effect Model

From the two-stage budgeting problem in the theoretical model, the derived health input demands are: $h_i = \dfrac{\partial C}{\partial p_i} = h^i(p, Y, \varepsilon_1, \varepsilon_2)$.

We will implement these demand functions by a system of estimation equations in (6a)-(6c):

$$Y_{it}^1 = \alpha_0 + \alpha_1 X_{1t} + \alpha_2 P_{it}^d + \alpha_3 P_{it}^o + \alpha_4 P_{it}^I + \alpha_5 Income + \mu_t + v_i + \varepsilon_{it}^1 \quad \text{(6a)}$$

$$Y_{it}^2 = \beta_0 + \beta_1 X_{1t} + \beta_2 P_{it}^d + \beta_3 P_{it}^o + \beta_4 P_{it}^I + \beta_5 Income + \mu_t + v_i + \varepsilon_{it}^2 \quad \text{(6b)}$$

$$Y_{it}^3 = \gamma_0 + \gamma_1 X_{1t} + \gamma_2 P_{it}^d + \gamma_3 P_{it}^o + \gamma_4 P_i^I + \gamma_5 Income + \mu_t + v_i + \varepsilon_{it}^3 \quad \text{(6c)}$$

Y^i denotes the demand for health input i, where $i = 1,2,3$ represents prescription drugs, outpatient services and inpatient services, respectively. X_1 denotes all observed non-price covariates. $P_{it}^d, P_{it}^o, P_{it}^I$ denote the price variables for prescription drugs, outpatient services and inpatient services at period t, respectively; $\mu_t (t = 1,2,3,4,5)$ captures the year trends; v_i captures the unobservable individual heterogeneity in demands for medical care. The individual heterogeneity is composed of individual specific idiosyncrasies ε_1 and ε_2 from the utility and production functions, respectively. ε_{it} is a random error which captures all other factors which affect the demands for medical care. It is widely believed in health economics literature that the unobserved individual heterogeneity is correlated with the drug price variables and other insurance variables in the demand equations. Therefore we treated the individual heterogeneity as fixed effect and estimate the above demand equations by a system of fixed effect models.

A problem with the Medstat data we used to estimate the health demands is that it doesn't have individual level income information. In a cross-sectional estimation framework omitting income variable from estimation could be problematic. Since income is almost certainly correlated with the price and insurance variables in the demand equations, omitting it from the demand equation will lead to biased estimates. However, in the fixed effect estimation framework, the consequence of leaving out income variable might not be as bad. Note that the population of Medstat data is employees and their dependents from large employers. The income effect for most individuals might be absorbed by individual fixed effects and time dummies. Fixed effect can't absorb all income effect for those who undergo dramatic change in income over time, such as the dependent spouses or teenage children. However, the dependent spouses don't show up in the Medstat database before they get married, and the teenage children will usually no longer stay in the Medstat database after their income starts to play an effect. Therefore the possible bias arising from omitting income variable for these people might be largely mitigated. The actual models we estimated after removing income variables are then:

$$Y_{it}^{1} = \alpha_0 + \alpha_1 X_{1t} + \alpha_2 P_{it}^{d} + \alpha_3 P_{it}^{o} + \alpha_4 P_{it}^{I} + \mu_t + v_i + \varepsilon_{it}^{1} \qquad (7a)$$

$$Y_{it}^{2} = \beta_0 + \beta_1 X_{1t} + \beta_2 P_{it}^{d} + \beta_3 P_{it}^{o} + \beta_4 P_{it}^{I} + \mu_t + v_i + \varepsilon_{it}^{2} \qquad (7b)$$

$$Y_{it}^{3} = \gamma_0 + \gamma_1 X_{1t} + \gamma_2 P_{it}^{d} + \gamma_3 P_{it}^{o} + \gamma_4 P_{i}^{I} + \mu_t + v_i + \varepsilon_{it}^{3} \qquad (7c)$$

In the above models demand responses to price changes are instantaneous. As mentioned above we conjecture that there could be both instantaneous and dynamic effects on health input demands resulting from price changes. One of our primary interests is to decompose the long term price effect from short term price effects on health input demands. In order to do so we added one period lagged prices to the demand functions to control for the long-term effects of price changes. The new demand equations are then:

$$Y_{it}^{1} = \alpha_0 + \alpha_1 X_{1t} + \alpha_2 P_{it}^{d} + \alpha_3 P_{it-1}^{d} + \alpha_4 P_{it}^{o} + \alpha_5 P_{it-1}^{o} + \alpha_6 P_{it}^{I} + \alpha_7 P_{it-1}^{I} + \mu_t + v_i + \varepsilon_{it}^{1} \quad (8a)$$

$$Y_{it}^{2} = \beta_0 + \beta_1 X_{1t} + \beta_2 P_{it}^{d} + \beta_3 P_{it-1}^{d} + \beta_4 P_{it}^{o} + \beta_5 P_{it-1}^{o} + \beta_6 P_{it}^{I} + \beta_7 P_{it-1}^{I} + \mu_t + v_i + \varepsilon_{it}^{2} \quad (8b)$$

$$Y_{it}^{3} = \gamma_0 + \gamma_1 X_{1t} + \gamma_2 P_{it}^{d} + \gamma_3 P_{it-1}^{d} + \gamma_4 P_{it}^{o} + \gamma_5 P_{it-1}^{o} + \gamma_6 P_{i}^{I} + \gamma_7 P_{it-1}^{I} + \mu_t + v_i + \varepsilon_{it}^{3} \quad (8c)$$

where $P_{it-1}^{d}, P_{it-1}^{o}, P_{it-1}^{I}$ are the lagged prices for prescription drugs, outpatient services and inpatient services from period t-1, respectively.

2. Serial Correlation and the Bootstrap Method for Standard Errors

Estimating health care demand using longitudinal data is in practice subject to potential serial correlation problem. Previous studies showed that patients' health status and thus health spending are persistent from one year to the next. (Eichner, McClellan and Wise [1996], Vliet [1992], Pauly and Zeng [2003]). The omission of relevant variables from the demand equation which aren't absorbed by the individual fixed effect could lead to serial correlation in error terms. Ignoring the serial correlation problem in estimation could potentially lead to severe bias in estimating the standard errors, and inference based on those standard error estimations would be wrong.

In practice most empirical studies that estimated FE models tend to ignore this problem and routinely estimate standard errors under the assumption of no serial correlation within groups. A survey by Kezdi (2002) showed that for the top three economic journals with a focus for applied empirical research, only 6 out of the 42 papers which estimated linear FE models took serial correlation into account when estimated the standard errors. The lack of empirical emphasis on this problem might be attributed to the lack of convenient statistical packages that specifically deal with problem of serial correlation within the fixed effect framework. However, theoretically both parametric and nonparametric solutions have been proposed to address this problem[4]. For example, Kiefer (1980), Bhargava et al. (1982) and Arellano (1987) proposed parametric robust standard error estimation methods to fix the problem of serial correlation in fix effect models. Bertrand, Duflo and Mullainathan (2002) used nonparametric block bootstrap method to estimate consistent standard errors at the presence of serial correlation in the Difference-in-Difference (DD) models. In their work it was stated that the block bootstrap method worked well in producing precise standard errors in the case when T is small and N is large.

Among the parametric and nonparametric methods proposed to fix the standard errors at the presence of serial correlation problem, we chose to use the block bootstrap method in this study. There are several reasons we believe this method may work best for our data. 1) Our panel data has the nature of small T and large N. There are about 332000 individuals in our data, and the average number of T is 2.6 for each person. In such case the block bootstrap method produces consistent standard error estimates in general. 2) The short time series in our data makes the use the parametric method problematic. It is difficult to identify the right assumption about the auto-correlation process and to precisely estimate the auto-correlation parameters using such a short time series. Instead, the bootstrap method has the merit of avoiding all parametric assumptions and approximations on the structure of error variance matrix. 3) The serial correlation problem and possible solutions to it for nonlinear panel models, such as fixed effect Poisson models and fixed effect Tobit models which we will estimate in this study, are still not fully explored in theory. Instead the block bootstrap method still works well for the nonlinear models, as long as these nonlinear models can estimate parameters

[4] For more discussion about the theoretical exploration of serial correlation in panel data models, see Bertrand, Duflo and Mullainathan (2004)

consistently at the presence of serial correlation, and sufficiently large N is guaranteed in the data.

3. Fixed-effect Count Data model

The above fixed effect models are linear regression models for the dependent variables. However, the discrete non-negative nature of some dependent variables in this study such as DAYSUPP (days of prescription supply), NUMV (number of outpatient visits) and NUMADM (number of admissions) suggests that the usual linear regression models may be inappropriate. [5] Instead the fixed effect Poisson models are considered in this study. There are several econometric approaches developed to estimate the fixed effect Poisson model. Hausman, Hall and Griliches (1984) proposed the conditional maximum likelihood estimator, and a non-linear GMM estimator was proposed by Montalvo (1993). In this study we adopted the HHG conditional maximum likelihood estimation for the fixed effect Poisson model.

In the HHG setup, the moment restriction used in estimating β is:

$$\lambda_{it} = \exp(c_i + \beta' x_{it}) = \exp(c_i)\exp(\beta' x_{it}) \,, \qquad \text{……………………..(10)}$$

where the fixed effect takes the multiplicative form $\exp(c_i)$. HHG showed that conditional on $\sum_{t=1}^{T} y_{it}$ for a given individual, the vector of y_i is jointly distributed as a multinomial distribution: $y_{i1,}...y_{iT} \mid \sum_{t=1}^{T} y_{it}, c_i, x_{it} \sim Multinomial\{\sum_{t=1}^{T} y_{it}, c_i, x_{it}\}$. The conditional probability is then: $p(y_{i1,}...y_{iT_i} \mid \sum_{t=1}^{T_i} y_{it}, c_i, x_{it}) = \left[\frac{(\sum_{t=1}^{T_i} y_{it})!}{\prod_{t=1}^{T} \mathrm{y}_{\mathrm{it}}!}\right] \prod_{t=1}^{T} \left[\frac{\exp(\beta' x_{it})}{\sum_{s=1}^{T_i} \exp(\beta' x_{is})}\right]^{y_{it}}$

The distribution of Daysupp shows the pattern of spikes at the points of 5n days, where n=1, 2, 3…. This suggests the fact that the normal duration of one prescription is a multiple of 5 days. Therefore it is reasonable to model the days of prescription supply as count data, rather than a continuous variable.

let $p_t(x_i, \beta) = \dfrac{\exp(\beta' x_{it})}{\sum_{s=1}^{T_i} \exp(\beta' x_{is})}$, then the conditional log likelihood function is

$L(\beta) = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \log[p_t(x_i, \beta)]$. The fixed effect Poisson estimator can be derived by maximizing this log likelihood function with respect to β. The estimated of marginal effect for variable x_k is $\dfrac{\partial E(y \mid x)}{\partial x_k} = \exp(\beta' x_{it} + c_i)\beta_k$.

This FE Poisson estimator has very strong robust properties. By Wooldridge, under only the conditional mean assumption, $\hat{\beta}_{FEP}$ is consistent even at the presence of serial correlation, or with overdispersion or underdispersion in the latent variable. Serial correlation in the error terms, and the possible overdispersion problem do, however, bias the estimation of $V(\hat{\beta}_{FE})$. The bootstrap method is again used to correct the standard error of parameter estimates.

4. Fixed effect Tobit model for Health Demand

The above section proposed the use of count data model for the quantity demand variables for days of prescription supply, number of outpatient visits and number of inpatient admissions. We also recognize that it is inappropriate to use linear regression models for the cost variables RXS (annual prescription drug spending), OUTS (annual outpatient spending) and INS (annual inpatient spending) either. Note that these cost variables are left censored at 0. Large numbers of zeroes are observed for the spending variables because some of the enrollees didn’t use any drug, outpatient or inpatient care within a particular year. We proposed the use of fixed effect Tobit models to estimate these spending variables. Although there has been a large number of literature on identification and estimation of linear panel data models with fixed effect, the fixed effect limited dependent models have not been studied as much. The most recent theoretical exploration on fixed effect Tobit estimation is by Honore (1994). He proposed a method to estimate Type I and Type II Tobit models by exploiting stationarity and exchangeability assumptions on the models' transitory error terms and constructed moment conditions that do not depend on the individual fixed effects. However, practically there aren't any convenient packages to estimate fixed effect Tobit models with large number of groups. As a result we have to estimate fixed effect Tobit models with broader fixed effects. (This will be explained in details in the following paragraph.) Again, the bootstrap method is used to correct the standard error of parameter estimates.

5. Individual Fixed Effects vs. Group Fixed Effects?

In the above sections, we proposed using fixed effect count data model to estimate the quantity demand variables such as NUMADM (number of admissions), and using the fixed effect Tobit model to estimate the spending variables. Ideally, we would like to use the fixed effect at the individual level in those nonlinear models to control for the individual heterogeneity in health demands. However, for the variable NUMADM, about 92% people in our sample never used any inpatient services in all years and 0.01% people used inpatient services in all years. These data are dropped from the individual fixed effect Poisson estimation. Since the dropped data isn't a random sample, we are concerned that parameter estimates from the conditional maximum likelihood estimation in the individual fixed effect Poisson model will not be representative for the whole population. Instead, it is very possible that the estimates will represent the demand response for the small group of older and sicker people that used hospital care in the study period. One way of eliminating the data-losing problem is to increase the length of panel by including more observations in a group. We define a broader group variable for the fixed effect by grouping people into age-gender-firm specific categories. We end up with 126 groups and are able to keep all data in the conditional MLE.

The data losing problem for other count variables such as NUMV (number of outpatient visits) and DAYSUPP (days of prescription supplies) wasn't as bad. There are about 11.8% non-users and 5.8% always-users for NUMV dropped in individual fixed effect Poisson model; 25% non-users and 4.4% always-users dropped for DAYSUPP. Considering the preciseness of individual fixed effect estimators compared with the broader group fixed effect estimators, we retain the individual fixed effect results for these two variables.

Secondly, we also estimated the Tobit model for spending variables by using the broader group fixed effect instead of individual fixed effect. This is due to a practical reason; in all existing statistical packages there isn't an easy, efficient way to estimate the fixed effect Tobit model with hundreds of thousands of groups. Considering both the computer capability to include dummy variables and the computation time it requires, we choose to use the group fixed effect in our Tobit model in estimating the spending variables.

V. Results

The estimation results are presented in **Table 4-Table10**. **Table 4-Table7** present the OLS and Tobit estimation results for the spending variables RXS, OUTS, INS and TOTS; **Table8-Table10** present the OLS and Poisson estimation results for the demand variables DAYSUPP, NUMV and NUMADM.

In each tables, we started with the simplest linear model using only contemporaneous drug price variable and the year dummies on the right hand side. The results from these simple OLS regressions are reported in column 1 of each table. In column 2 of each table, we present the results of OLS regression with contemporaneous drug price and insurance variables, and all other non-price covariates; Column 3 reports the OLS results by adding the lagged drug prices and insurance variables. We call this model the full structure linear model. For all OLS results we report the point estimate of coefficients and the bootstrapped standard errors for those parameters. The results for FE Tobit model are reported in columns 5 and 6 of **Table 4** – **Table7**. In column 4 & column 5 of **Table8-Table10**, we report results for FE Poisson models. For both Tobit and Poisson models we report the marginal effect of each variable and the bootstrapped standard error for them.

Table4: OLS and Tobit Estimation Results for Prescription Drug Spending

	OLS		OLS		OLS		OLS		Tobit		Tobit	
	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Marginal Effect	Bootstrap Std	Marginal Effect	Bootstrap Std
RxP	-9.54	1.12	-9.76	1.28	-11.14	1.28	-10.39	1.19	-12.68	1.03	-9.71	0.90
RxP_1	–	–	–	–	-13.86	1.20	-11.14	1.58	–	–	-8.35	1.02
Deduct	–	–	0.17	0.04	0.17	0.04	0.15	0.04	-0.20	0.03	-0.10	0.03
Deduct_1	–	–	–	–	0.22	0.06	0.03	0.09	–	–	-0.20	0.06
Copay	–	–	7.48	1.38	13.68	1.38	12.91	1.16	18.77	1.11	20.57	1.02
Copay_1	–	–	–	–	11.13	3.33	-1.38	3.66	–	–	-4.13	2.38
Maxoop	–	–	0.00	0.01	0.00	0.01	0.02	0.01	0.08	0.01	0.06	0.01
Maxoop_1	–	–	–	–	-0.01	0.02	0.02	0.02	–	–	0.03	0.01
Urban	–	–	-20.2	13.7	-9.34	13.84	-1.78	9.01	-32.58	6.19	-31.41	6.21
Retire	–	–	-4.28	14.5	8.43	14.49	93.20	13.29	57.73	8.56	58.22	8.59
Married	–	–	-24.3	11.7	-26.70	11.69	-106	8.97	-45.04	5.64	-45.10	5.65
Age1time	–	–	-152	2.78	-144	2.80	-173	6.00	-105	4.02	-98.78	4.02
Age2time	–	–	-143	2.84	-135	2.89	-156	5.65	-78.03	4.09	-72.31	4.08
Age3time	–	–	-136	3.11	-130	3.14	-162	7.21	-89.26	4.99	-84.16	4.99
Age4time	–	–	-107	3.13	-99.2	3.02	-142	6.13	-75.29	4.32	-68.57	4.22
Age5time	–	–	-75.8	3.10	-69.3	3.07	-101	7.57	-51.02	4.66	-45.19	4.67
Age6time	–	–	-30.57	2.35	-27.14	2.35	-45.11	7.68	-25.55	4.75	-22.77	4.73
Year01	353	5.00	579	8.85	628	9.94	660	19.37	378	13.50	401	14.56
Year00	245	3.15	379	5.63	425	7.49	437	13.67	226	8.44	250	9.28
Year99	119	2.42	192	3.25	232	5.57	237	8.76	122	4.28	146	5.81
_cons	452	–	608	–	603	–	538	–	–	–	–	–
N	847801		847801		847801		847801		847801		847801	
N_Group	331689		331689		331689		126		126		126	
R-Square	0.024		0.032		0.032		0.06		0.008		0.008	
Loglikelihood/ F-test	3224		1061.51		858.87		1460		-5287781		-5287741	
Fixed Effect	**Individual**		**Individual**		**Individual**		**Group**		**Group**		**Group**	

Table5: OLS and Tobit Estimation Results for Outpatient Care Spending

	OLS		OLS		OLS		OLS		Tobit		Tobit	
	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Marginal Effect	Bootstrap Std	Marginal Effect	Bootstrap Std
RxP	−18.03	5.34	−16.94	5.94	−17.10	6.51	−9.64	4.71	−4.22	3.59	−6.46	3.45
RxP_1	–	–	–	–	38.45	5.14	29.20	4.81	–	–	13.03	2.99
Deduct	–	–	−0.09	0.17	−0.24	0.19	−0.20	0.13	−0.31	0.11	−0.21	0.10
Deduct_1	–	–	–	–	−0.83	0.30	0.89	0.22	–	–	0.71	0.14
Copay	–	–	−17.77	4.69	−35.00	4.94	−23.42	3.31	17.50	2.45	−2.00	2.27
Copay_1	–	–	–	–	−8.53	14.69	88.42	10.87	–	–	87.39	6.99
Maxoop	–	–	0.02	0.05	0.04	0.06	0.05	0.05	0.06	0.03	0.01	0.03
Maxoop_1	–	–	–	–	0.12	0.08	0.47	0.07	–	–	0.39	0.04
Urban	–	–	78.80	45.53	48.33	45.53	62.24	25.20	41.03	12.94	34.70	13.01
Retire	–	–	177	91.80	142	91.80	64.36	41.43	10.23	30.24	5.82	30.23
Married	–	–	−9.43	60.08	−5.37	59.99	−144	18.41	−34.59	13.54	−33.79	13.55
Age1time	–	–	−310	16.48	−332	16.83	−321	24.13	−188	13.78	−202	13.86
Age2time	–	–	−283	16.33	−303	16.81	−317	24.27	−166	13.63	−179	13.52
Age3time	–	–	−274	17.75	−291	18.09	−332	30.29	−235	17.43	−247	17.40
Age4time	–	–	−193	17.92	−212	18.04	−240	27.92	−142	15.24	−157	15.26
Age5time	–	–	−148	16.43	−165	16.70	−188	28.88	−100	15.24	−115	15.11
Age6time	–	–	−79	14.17	−88.47	14.10	−123	22.47	−69.08	14.95	−77	14.90
Year01	736	20.26	1176	46.63	1038	50.45	1049	71.08	708	40.94	678	43.11
Year00	434	13.30	743	31.62	618	36.26	628	49.13	420	25.00	389	28.42
Year99	140	9.56	272	16.29	156	21.76	190	25.99	185	13.82	131	17.00
_cons	1410	–	1751	–	1543	–	648	–	–	–	–	–
N	847801		847801		847801		847801		847801		847801	
N_Group	331689		331689		331689		126		126		126	
R-Square	0.005		0.007		0.007		0.023		0.002		0.002	
Loglikelihood/ F-test	677.5		211.29		171.93		4635		−7075654.7		−5287741	
Fixed Effect	**Individual**		**Individual**		**Individual**		**Group**		**Group**		**Group**	

Table6: OLS and Tobit Estimation Results for Inpatient Care Spending

	OLS		OLS		OLS		OLS		Tobit		Tobit	
	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Marginal Effect	Bootstrap Std	Marginal Effect	Bootstrap Std
RxP	−14.05	12.74	−22.60	14.71	−15.10	14.92	−7.33	8.89	0.79	4.31	−3.39	4.43
RxP_1	–	–	–	–	45.83	8.60	36.64	9.62	–	–	10.71	4.24
Deduct	–	–	−0.57	0.48	−0.36	0.35	−0.10	0.47	0.40	0.15	0.35	0.16
Deduct_1	–	–	–	–	−0.35	0.61	0.35	0.34	–	–	0.03	0.18
Copay	–	–	−5.55	8.74	−26.95	10.12	−13.08	7.75	−2.57	2.63	−1.35	3.37
Copay_1	–	–	–	–	−35.00	52.87	−1.61	13.38	–	–	−4.96	6.70
Maxoop	–	–	0.17	0.15	0.08	0.11	0.02	0.16	−0.12	0.05	−0.12	0.05
Maxoop_1	–	–	–	–	−0.17	0.44	−0.03	0.12	–	–	−0.02	0.05
Urban	–	–	−31.58	108	−72.36	108.84	−57.95	27.79	−71.39	15.84	−72.73	15.94
Retire	–	–	−72.72	227	−117	227.13	−9.26	73.07	−12.70	28.58	−13.71	28.74
Married	–	–	47.96	112	56.43	112.21	−21.77	25.92	55.10	11.51	55.23	11.52
Age1time	–	–	−219	25.87	−246	26.48	−219	36.64	−82.69	25.24	−91.28	25.87
Age2time	–	–	−201	26.04	−227	26.54	−217	35.85	−46.17	19.68	−53.44	20.98
Age3time	–	–	−201	25.46	−223	26.40	−207	39.21	−97.84	22.31	−105	23.23
Age4time	–	–	−152	27.12	−177	27.57	−134	33.56	−28.20	12.71	−36.72	12.53
Age5time	–	–	−113	23.19	−135	23.41	−134	41.75	−5.13	14.28	−12.43	15.34
Age6time	–	–	−72.42	28.84	−84.04	29.25	−59.16	45.42	−17.03	11.71	−20.78	12.41
Year01	382	53.70	723	78.03	561	79.91	483	90.11	165	36.34	139	37.07
Year00	204	27.78	443	49.50	294	54.76	247	62.36	95.38	23.85	63.99	25.08
Year99	14.64	22.78	116	30.82	−13.92	34.75	−2.25	40.84	22.83	16.78	−2.12	19.98
_cons	678	–	884	–	1217	–	517	–	–	–		–
N	847801		847801		847801		847801		847801		847801	
N_Group	331689		331689		331689		126		126		126	
R-Square	0.0004		0.0006		0.0006		0.005		0.014		0.014	
Loglikelihood/ F-test	53.13		19.08		16.48		6984		−564254		−564250	
Fixed Effect	**Individual**		**Individual**		**Individual**		**Group**		**Group**		**Group**	

Table7: OLS and Tobit Estimation Results for Total Spending

	OLS		OLS		OLS		OLS		Tobit		Tobit	
	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Marginal Effect	Bootstrap Std	Marginal Effect	Bootstrap Std
RxP	-41.63	12.70	-49.30	13.83	-43.34	13.65	-27.36	10.76	-14.12	7.28	-20.59	7.35
RxP_1	-	–	-	-	70.42	10.97	54.70	11.73	-	-	22.85	7.27
Deduct	-	-	-0.49	0.47	-0.44	0.37	-0.15	0.54	-0.37	0.25	-0.32	0.30
Deduct_1	-	-	-	-	-0.95	0.84	1.27	0.48	-	-	1.02	0.28
Copay	-	-	-15.84	11.49	-48.27	13.82	-23.58	8.26	30.74	5.60	9.01	5.84
Copay_1	-	-	-	-	-32.40	59.17	85.43	21.17	-	-	101.61	12.51
Maxoop	-	-	0.18	0.16	0.13	0.11	0.09	0.18	0.08	0.09	0.03	0.10
Maxoop_1	-	-	-	-	-0.06	0.50	0.46	0.14	-	-	0.43	0.09
Urban	-	-	27.04	147	-33.36	147.60	2.51	40.21	-6.32	28.13	-14.75	28.21
Retire	-	-	100	229	33.55	227.97	148	99.22	69.01	59.11	62.97	59.25
Married	-	-	14.27	133	24.36	133.09	-270	38.80	-38.53	23.17	-37.38	23.24
Age1time	-	-	-681	33.59	-722	35.18	-714	53.96	-407	26.30	-430	27.08
Age2time	-	-	-627	34.47	-665	35.96	-691	51.21	-362	27.35	-383	28.80
Age3time	-	-	-611	37.96	-643	39.18	-701	67.57	-445	33.43	-464	33.70
Age4time	-	-	-451	34.52	-488	35.68	-516	57.28	-298	28.07	-322	28.68
Age5time	-	-	-337	35.80	-370	36.55	-423	62.90	-222	33.96	-245	35.48
Age6time	-	-	-182	27.15	-200	27.39	-228	55.40	-125	34.03	-137	34.04
Year01	1471	46.63	2479	98.34	2227	99.38	2191	152.24	1422	80.22	1369	81.90
Year00	883	28.07	1565	62.00	1337	64.87	1312	104.15	848	51.84	788	55.69
Year99	273	24.97	580	36.87	374	43.62	425	62.84	367	29.36	283	37.67
_cons	2540	–	3243	-	3363	-	1703	-	-	-	-	-
N	847801		847801		847801		847801		847801		847801	
N_Group	331689		331689		331689		126		126		126	
R-Square	0.004		0.005		0.005		0.02		0.002		0.002	
Loglikelihood/ F-test	472.72		153.65		124.62		9728		-7897592		-7897550	
Fixed Effect	**Individual**		**Individual**		**Individual**		**Group**		**Group**		**Group**	

Table8: OLS and Poisson Estimation Results for Days of Supply for Prescription Drugs

	OLS		OLS		OLS		Poisson		Poisson	
	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Marginal Effect	Bootstrap Std	Marginal Effect	Bootstrap Std
RxP	-2.47	0.31	-3.08	0.35	-4.36	0.34	-3.49	0.50	-4.96	0.47
RxP_1	-	–	-	-	-5.61	0.31	-	-	-0.29	0.35
Deduct	-	-	0.02	0.01	0.00	0.01	0.01	0.01	-0.03	0.01
Deduct_1	-	-	-	-	-0.02	0.02	-	-	-0.14	0.03
Copay	-	-	2.35	0.26	4.98	0.31	0.79	0.34	1.16	0.40
Copay_1	-	-	-	-	1.56	0.31	-	-	-0.40	1.05
Maxoop	-	-	0.01	0.00	0.02	0.00	0.00	0.00	0.01	0.00
Maxoop_1	-	-	-	-	0.00	0.00	-	-	0.00	0.00
Urban	-	-	-20.99	4.50	-16.31	4.50	2.33	3.04	2.37	2.90
Retire	-	-	3.68	4.94	8.76	4.92	-12.82	3.38	-12.63	3.82
Married	-	-	2.78	3.75	1.69	3.76	18.75	3.91	18.53	3.71
Age1time	-	-	-56.75	0.88	-53.38	0.91	4.41	2.07	4.87	2.39
Age2time	-	-	-54.09	0.88	-50.92	0.91	8.21	1.42	8.62	1.57
Age3time	-	-	-50.11	0.99	-47.45	1.01	4.09	1.63	4.42	1.64
Age4time	-	-	-38.34	0.87	-35.30	0.88	14.80	1.08	15.11	1.09
Age5time	-	-	-29.28	0.87	-26.56	0.86	9.97	0.87	10.29	0.69
Age6time	-	-	-11.39	0.69	-9.94	0.68	3.93	0.43	4.08	0.48
Year01	122	1.38	206	2.64	226	2.91	147	2.03	149	1.57
Year00	84.82	0.89	136	1.86	155	2.17	94.48	1.44	96.34	1.29
Year99	40.53	0.75	67.32	1.11	83.55	1.60	43.64	0.95	44.01	0.88
_cons	265	–	328	-	354	-	-	-	-	-
N	847801		847801		847801		680591		680591	
N_Group	331689		331689		331689		257844		257844	
R-Square	0.046		0.062		0.063		-		-	
Loglikelihood/ F-test	6227		2140.23		1743.32		-18729658		-18719495	
Fixed Effect	**Individual**		**Individual**		**Individual**		**Individual**		**Individual**	

Table9: OLS and Poisson Estimation Results for Number of Outpatient Visits

	OLS		OLS		OLS		Poisson		Poisson	
	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Point Estimate	Bootstrap Std	Marginal Effect	Bootstrap Std	Marginal Effect	Bootstrap Std
RxP	0.11	0.03	-0.09	0.03	-0.15	0.04	-0.17	0.03	-0.24	0.05
RxP_1	–	–	–	–	0.10	0.03	–	–	0.05	0.03
Deduct	–	–	0.00	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00
Deduct_1	–	–	–	–	-0.01	0.00	–	–	-0.01	0.00
Copay	–	–	0.14	0.02	0.10	0.02	0.11	0.02	0.09	0.02
Copay_1	–	–	–	–	0.14	0.02	–	–	0.08	0.11
Maxoop	–	–	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maxoop_1	–	–	–	–	0.00	0.00	–	–	0.00	0.00
Urban	–	–	0.76	0.27	0.72	0.27	0.55	0.35	0.54	0.28
Retire	–	–	0.35	0.45	0.28	0.45	-0.09	0.35	-0.11	0.33
Married	–	–	0.54	0.31	0.53	0.31	0.71	0.28	0.69	0.29
Age1time	–	–	-1.74	0.07	-1.79	0.07	-1.37	0.09	-1.38	0.09
Age2time	–	–	-1.43	0.07	-1.47	0.07	-0.69	0.08	-0.70	0.09
Age3time	–	–	-1.62	0.07	-1.66	0.07	-1.11	0.08	-1.13	0.09
Age4time	–	–	-1.09	0.06	-1.13	0.07	-0.55	0.07	-0.56	0.07
Age5time	–	–	-0.80	0.06	-0.84	0.06	-0.33	0.06	-0.34	0.05
Age6time	–	–	-0.46	0.05	-0.48	0.06	-0.21	0.04	-0.22	0.04
Year01	3.06	0.09	5.67	0.17	5.28	0.21	4.89	0.16	4.68	0.20
Year00	1.94	0.07	3.59	0.12	3.25	0.15	3.02	0.11	2.84	0.15
Year99	1.07	0.06	1.86	0.07	1.48	0.10	1.65	0.08	1.43	0.10
_cons	12.89	–	16.13	–	10.82	–	–	–	–	–
N	847801		847801		847801		783020		783020	
N_Group	331689		331689		331689		303418		303418	
R-Square	0.004		0.006		0.006		–		–	
Loglikelihood/ F-test	571.16		203.87		167.26		-2886379		-2885730	
Fixed Effect	**Individual**		**Individual**		**Individual**		**Individual**		**Individual**	

Table10: OLS and Poisson Estimation Results for Number of Inpatient Admissions

	OLS		OLS		OLS		Poisson		Poisson		Poisson		Poisson	
	Point Estimate	Bstrap Std	Point Estimate	Bstrap Std	Point Estimate	Bstrap Std	Marginal Effect	Bstrap Std	Marginal Effect	Bstrap Std	Marginal Effect	Bstrap Std	Marginal Effect	Bstrap Std
RxP	0.000	0.001	-0.001	0.000	-0.0005	0.0005	-0.007	0.004	-0.006	0.005	0.0001	0.0005	-0.0034	0.0004
RxP_1	-	–	-	-	0.0016	0.0005	-	-	0.015	0.004	-	-	0.0078	0.0004
Deduct	-	-	0.000	0.000	0.0000	0.0000	0.000	0.000	0.000	0.000	0.0003	0.0000	0.0003	0.0000
Deduct_1	-	-	-	-	0.0000	0.0000	-	-	0.000	0.000	-	-	0.0000	0.0000
Copay	-	-	0.000	0.000	-0.0003	0.0004	0.003	0.004	-0.004	0.004	-0.0027	0.0002	-0.0005	0.0003
Copay_1	-	-	-	-	-0.0001	0.0004	-	-	0.001	0.012	-	-	-0.0077	0.0007
Maxoop	-	-	0.000	0.000	0.0000	0.0000	0.000	0.000	0.000	0.000	-0.0001	0.0000	-0.0001	0.0000
Maxoop_1	-	-	-	-	0.0000	0.0000	-	-	0.000	0.000	-	-	0.0000	0.0000
Urban	-	-	-0.006	0.005	-0.0070	0.0048	-0.022	0.036	-0.031	0.035	-0.0333	0.0012	-0.0342	0.0015
Retire	-	-	-0.004	0.007	-0.0052	0.0068	-0.031	0.046	-0.045	0.045	-0.0031	0.0029	-0.0039	0.0031
Married	-	-	0.000	0.005	0.0004	0.0051	0.004	0.029	0.006	0.028	0.0203	0.0010	0.0204	0.0010
Age1time	-	-	-0.009	0.001	-0.0096	0.0011	-0.081	0.019	-0.091	0.021	-0.0608	0.0022	-0.0669	0.0020
Age2time	-	-	-0.007	0.001	-0.0079	0.0011	-0.020	0.012	-0.029	0.016	-0.0371	0.0019	-0.0425	0.0020
Age3time	-	-	-0.008	0.001	-0.0084	0.0011	-0.041	0.012	-0.049	0.011	-0.0655	0.0017	-0.0707	0.0018
Age4time	-	-	-0.007	0.001	-0.0083	0.0011	-0.045	0.009	-0.054	0.008	-0.0228	0.0011	-0.0291	0.0012
Age5time	-	-	-0.007	0.001	-0.0073	0.0010	-0.037	0.007	-0.044	0.007	0.0018	0.0013	-0.0034	0.0014
Age6time	-	-	-0.003	0.001	-0.0036	0.0010	-0.011	0.005	-0.014	0.006	-0.0111	0.0011	-0.0137	0.0010
Year01	0.009	0.002	0.024	0.003	0.0183	0.0031	0.156	0.021	0.106	0.023	0.0931	0.0025	0.0775	0.0026
Year00	0.006	0.001	0.016	0.002	0.0103	0.0026	0.097	0.014	0.052	0.017	0.0631	0.0019	0.0408	0.0019
Year99	-0.000	0.001	0.005	0.001	-0.0004	0.0022	0.018	0.012	-0.021	0.013	0.0084	0.0014	-0.0076	0.0012
_cons	0.055	–	0.076	-	0.0543	-	-	-	-	-	-	-	-	-
N	847801		847801		847801		91525		91525		847801		847801	
N_Group	331689		331689		331689		33338		33338		126		126	
R-Square	0.0002		0.0004		0.004		-		-		0.05		0.05	
Loglikelihood/ F-test	23.47		12.36		10.74		-410010		-40998		-190305		-190298	
Fixed Effect	**Individual**		**Individual**		**Individual**		**Individual**		**Individual**		**Group**		**Group**	

Results for Spending Equations

The results for estimating RXS, OUTS, INS and TOTS are reported in **TABLE4-TABLE7**, respectively. Our primary interests are centered on the parameter estimates of contemporaneous and lagged drug prices. First, let's look at the simple OLS models with only contemporaneous drug prices. In column (1) to (2) of **TABLE 4**, the coefficient of contemporaneous drug prices from the OLS estimation have the expected negative sign, and are consistently significant at 5% level by the bootstrapped standard error. Adding control variables from the model in column (1) to model in column (2) doesn't significantly change the size of effect. In column (1) & (2) of **TABLE5-TABLE6** where OUTS and INS equations are estimated, the OLS results strongly suggest that outpatient services and inpatient services are complements to prescription drugs. Contemporaneous drug prices have negative and significant coefficients on the spending on outpatient and inpatient services. Specifically, a dollar increase in drug price will reduce total outpatient spending by $16.94, and inpatient spending by $22.60. Overall one dollar increases in prescription drug cost-sharing reduce the total spending by $49.30.

Based on the above results, one might conclude that outpatient and inpatient services are complements for prescription drugs in consumption. The increase of prescription drug cost-sharing could reduce moral hazard and excessive consumption not only on prescription drugs, but also on consumption of its complementary medical services. In recent years insurance policy makers have been battling diligently with the fast-rising healthcare costs by increasing the stake of the patients in cost-sharing of prescription drugs. It seems that they made the right choice. But, is it true?

The above conclusion will be overturned by further analysis by adding lagged drug prices into all the spending equations. We reported the OLS results for spending equations with lagged drug prices in column (3) of **TABLE4-TABLE7**. In **TABLE4**, the lagged drug price reduce drug spending (RXS) by $13.86. In column (3) of **TABLE6-TABLE7**, the coefficients of contemporary drug prices are still consistently negative and significant, suggesting the complement relationship between these medical services and prescription drugs. However, the striking findings are about the lagged drug prices effects in column (3). Now the coefficients of lagged drug prices are positive and significant on outpatient and inpatient spending. This implies that patients respond to the increased cost-sharing of prescription drugs by increasing the outpatient and inpatient consumptions in the next year after the price changes. Reading rough estimates from linear FE model in column (3), a one dollar increase in drug cost-sharing reduces the outpatient and inpatient spending by $17.10 and $15.10 respectively in the year of price changes; however in the year after the price changes it increases them by $38.45 and $45.83, respectively. These findings suggest a very strong dynamic substituting effect on outpatient and inpatient consumptions resulting from the price changes in prescription drugs. Because of these substitution effects, the aggregate price effects from increased cost-sharing became negative. According to the OLS estimates, a dollar increase in drug cost-sharing reduces total medical spending in the short-run by $43.34, but increases it in the long-run by $70.42. The net effect is about $27 increase in total spending.

Other variables are of less interest, and are included as control variables in the spending equations. However, some points are worth making for the results of the control variables in the OLS FE models: for the insurance variables, increase in deductibles (DEDUCT) and copayments (COPAY) will increase total drug spending. Maximum out of pocket limit (MAXOOP) has no effect on the drug spending. Also note that the set of interaction variables (AGE1YEAR-AGE6YEAR) are consistently significant. The demand for prescription drugs of older people grows faster than the younger ones over years, and this finding might indicate that the health status of older people deteriorates at a higher rate than the younger people.

Now let's move on with the results of Tobit models for RXS, OUTS, INS and TOTS. Those results are reported in column (5) & (6) of **TABLE4-TABLE7**. Note that we estimated group fixed effect Tobit model instead of the individual fixed effect Tobit model. Comparing column(3) &(6), (2)&(5) in **TABLE 4- TABLE7**, it is clear that the fixed effect Tobit estimation follows a similar pattern to its linear comparables in all four spending equations, except that it produces much smaller parameter estimates for the drug price variables. Let's focus on comparing the full models of both linear and Tobit model represented by column (3) & (6). For RXS equation, the coefficients for both contemporary drug price and lagged drug prices are both negative and significant. In the OUTS and INS equations of the Tobit model, the contemporary drug price is negative and lagged drug price positive, suggesting that outpatient and inpatient services are short-term complements to prescription drugs, but long-term substitutes. Moreover, again the long-term price effects dominate the short-term price effect. However, the sizes of price effects in all RXS, OUTS, INS and TOTS models shrink substantially in the Tobit model compared with the OLS model. Now in the group fixed effect Tobit model, a $1 increase in drug cost-sharing will reduce drug spending, outpatient spending, inpatient spending and total spending by $9.71, $6.46, $3.39 and $20.59 respectively in the year of price changes. In the following the price changes, the drug spending will decrease by $8.35, but outpatient, inpatient and total spending will increase by $13.03, $10.71 and $22.85, respectively. The dramatic difference between Tobit and OLS esimates is not surprising. Note that we observe large number of zeros in all the spending variables. The OLS fixed effect estimation is in essential a mean differenced OLS estimation. The big jumps in spending from nonuser to user, or vice versa, might lead to large within variations in the fixed effect model, and therefore inflate the parameter estimates for price variables. Our finding might suggest that the conventionally OLS fixed effect model over-estimates the demand responses.

However, the Tobit estimates we got might not be perfectly accurate either. Since we are moving from the individual fixed effect OLS model onto the group fixed effect Tobit model due to the limitation of statistical software, the change in parameter estimates in the Tobit model could compound the effects from using the broader fixed effect and Tobit model itself.

For the purpose of comparison, we included the regression results from Group fixed effect OLS model in column (4) of **TABLE4-TABLE7**. It is clear that the group fixed effect OLS produces smaller coefficients than the individual fixed effect OLS models for all four spending equations. This phenomenon seems a reasonable result of the group fixed effects. In the group fixed effect models, we have a much smaller panel within our sample, but a much longer time series within each panel. The within variation among groups were smoothed out somewhat by the averaging of more data points within panel, and therefore the group fixed effect parameter estimates are supposed to be smaller than the individual fixed effect model, holding everything else unchanged. However, more careful examinations are needed for assessing the direction of bias from using group fixed effect for the both the linear fixed effect models and nonlinear fixed effect Tobit model.

Results for Quantity Equations

From **TABLE8-TABLE10**, we see that the results for quantity demand equations DAYSUPP, NUMV and NUMADM follow a very similar pattern as the spending equations. In the OLS models, increased cost-sharing in prescription drugs reduces the number of days of prescription supply (DAYSUPP), number of outpatient visits (NUMV) and number of hospital admissions (NUMADM) in the short-run. However, in the long-run both NUMV and NUMADM increase, confirming again our conclusion of short-term complements and long-term substitutes.

The results for individual fixed effect Poisson models are reported in column (4) & (5). Moreover, we reported the results of the group fixed effect model two additional columns (6)&(7) for NUMADM. For these Poisson models, marginal effects and the corresponding bootstrap standard errors are reported. In **Table 8** for the DAYSUPP equation, the short-term price effect on drug supply days is -4.96, and the estimate for lagged price effect is -0.29; in **TABLE9**, the marginal effect of contemporary and lagged drug prices on NUMV is -0.24 and 0.05, respectively; in **TABLE10** where the results for individual fixed effect Poisson are reported in Column (4) & (5), the contemporary and lagged drug price effect on NUMADM is -0.006 and 0.015, respectively.

Interestingly, for these quantity equations the sizes of lagged drug price effects no longer dominate the contemporary price effects, as is true in the spending equations. How does one explain the inconsistency in the estimated price effects between spending equations and quantity equations? Note that the quantity variables are very rough measures compared with spending variables. For example, in constructing the NUMV variable, a regular doctor visit is counted the same as a MRI test. Similarly, in the NUMADM variable, a minor car accident injury admission is counted the same as an admission of heart attack, so each count of either outpatient and inpatient quantity does not have even weights. The inconsistency in the spending and quantity estimates might serve as an indicator that in the long run, the underutilization of prescription drugs resulting from increased drug cost-sharing caused the increasing of expensive outpatient visits and inpatient admissions, such as emergency room use or heart attack admission.

In **TABLE10** of NUMADM, the individual fixed effect Poisson results in column (4) & (5), and the group fixed effect Poisson results in column (6) & (7) follow similar patterns, except that the group FE estimates for contemporaneous and lagged drug price are consistently smaller than the individual FE estimates in both models with or without lagged price. One possible explanation for this result is, the data used for the individual FE estimation is a selective sample of sicker and older people who ever used inpatient services (only 8% out of all of the enrollees), and data used for the group FE estimation include the whole population, which on average, represents a younger and healthier sample. Then the difference between the point estimates from the individual FE model and group FE model might suggest that the sicker people are more price responsive than the average people in the population. As drug copayment goes up, the older and sicker people reduce hospital care more than the younger people do in the short run. However, the under-utilization of prescription drugs and inpatient services as the result of increased cost-sharing on prescription drugs is likely to put the sicker people at higher risks in the long-run (0.015 increase in hospital admission vs. 0.008 for the population average).

VI. Conclusion

In this paper we studied the substitute-complement relationship between prescription drugs and two other distinct health inputs, outpatient and inpatient care. We addressed the econometric issues with the fixed effect model and the specific data used in this study. Our results show that a one dollar increase in the consumer copayment for drugs has the following effects: 1.) In the first year after the change, drug spending, outpatient spending, inpatient spending, and total spending fall by $9.71, $6.46, $3.39, and $20.39, respectively. 2.) In the second year after the change, drug spending falls by $8.35, while inpatient spending, outpatient spending, and overall spending rise by $10.71, $13.03, and $22.85, respectively. This amounts to a 0.75% decrease in total spending in the first year and a 0.84% increase in spending in the second. As is evident, there are both dynamic and instantaneous effects from changes in consumer drug copayments. Raising consumer drug copayment by $1 per prescription actually

raises overall spending by about $1 per enrollee per year over two years (ignoring discounting). This implies that more generous prescription drug benefits may be costly in the short run, but can generate cost savings in the long run. These long run effects should be taken into account when estimating the expected cost of programs like the Medicare prescription drug benefits which will be implemented beginning January 2006. Compared to the drug benefits in the 9 large employers in our data, Medicare's drug benefits are the most stringent. Medicare beneficiaries have to pay the first $250 deductible in drug costs, 25% of total drug costs between $250 and $2250, 100% of drug costs between $2250 and $5100, and 5% after reach the $3600 out-of-pocket limit. The findings from our study suggest that this high cost-sharing structure might not be optimally designed. It might result in more utilization and spending on hospital and outpatient care for Medicare beneficiaries in the long run, and might not reach the ultimate cost-saving goal.

Future research can be directed to examine both the contemporaneous and dynamic substitute-complement relationships among medical inputs for specific medical conditions and demographic groups.

Appendix 1

This appendix is to proof that the size of substitution in consumption is smaller than the substitution in production.

Let $MRS(X,H,\varepsilon_1) = \dfrac{\partial U(X,H,\varepsilon_1)/\partial H}{\partial U(X,H,\varepsilon_1)/\partial X}$, for a quasi-concave utility function, we will get $\dfrac{\partial MRS(X,H,\varepsilon_1)}{\partial X} \geq 0$, and $\dfrac{\partial MRS(X,H,\varepsilon_1)}{\partial H} \leq 0$.

From equation (2), the FOC of the utility maximization problem, we have:

$$F = MRS(Y-C,H,\varepsilon_1) - \partial C(p,H,\varepsilon_2)/\partial H$$

By the implicit function theory,

$$\frac{\partial H}{\partial p_j} = -\frac{\partial F/\partial p_j}{\partial F/\partial H} = -\frac{-\dfrac{\partial MRS}{\partial X}\cdot\dfrac{\partial C}{\partial p_j} - \dfrac{\partial^2 C}{\partial H \partial p_j}}{-\dfrac{\partial MRS}{\partial X}\cdot\dfrac{\partial C}{\partial H} + \dfrac{\partial MRS}{\partial H} - \dfrac{\partial^2 C}{\partial H^2}} = -\frac{\dfrac{\partial MRS}{\partial X}\cdot\dfrac{\partial C}{\partial p_j} + \dfrac{\partial^2 C}{\partial H \partial p_j}}{\dfrac{\partial MRS}{\partial X}\cdot\dfrac{\partial C}{\partial H} - \dfrac{\partial MRS}{\partial H} + \dfrac{\partial^2 C}{\partial H^2}}$$

…………………………………………………………. (6)

It is straightforward that $\dfrac{\partial C}{\partial H} > 0$.

Given the assumption that the production technology is homothetic, we can write the cost function as $C(H,p,\varepsilon_2) = \alpha \cdot H \cdot C(1,p,\varepsilon_2)$, where α is a constant. Then we have $\dfrac{\partial^2 C}{\partial H^2} = 0$.

Given C is the cost function of a single-output technology H with production function ψ, C is a concave function of p. Therefore, $\partial C(p,H,\varepsilon_2)/\partial p_j > 0$.

It is also easy to prove that $\dfrac{\partial^2 C}{\partial H \partial p_j} = \dfrac{\partial C(1,p,\varepsilon_2)}{\partial p_j} > 0$.

Then both the denominator and numerator in equation (6) are positive. So $\dfrac{\partial H}{\partial p_j} < 0$.

Also, $\dfrac{\partial h^i}{\partial H} > 0$.

$$\Rightarrow \frac{\partial h^i}{\partial H} \cdot \frac{\partial H}{\partial p_j} < 0$$

$$\frac{\partial h^i}{\partial p_j} = \frac{\partial h^i}{\partial p_j}\Big|_{H=\bar{H}} + \frac{\partial h^i}{\partial H} \cdot \frac{\partial H}{\partial p_j} < \frac{\partial h^i}{\partial p_j}\Big|_{H=\bar{H}} \qquad (7)$$

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