New Estimates of the Elasticity of Demand for Prescription Drugs among the US Adult Population

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1. Introduction

Within most OECD countries pharmaceutical expenditures as a percentage of total health expenditures have been rising at a much faster rate than increases in other types of health expenditures over the past decade (OECD 2005). In response, policymakers and third-party payers have applied various cost-containment tools along the pharmaceutical distribution chain (Light and Walley 2004), including cost sharing, which targets the consumers of prescription drugs and mainly appears as co-payments, coinsurance, and deductibles[1]. Most third-party payers in the developed world employ some form of cost sharing for prescription drugs, although the types of cost sharing, the burden placed on users, and the exempt populations differ by country.

One of the main aims of cost sharing is to increase efficiency by combating the excessive use of medical care that arises when individuals are fully insured (Kutzin 1998). In terms of prescription drugs, when consumers possess supplementary drug insurance, they are shielded from the full cost of their medications. This may induce them to consume medications where the marginal cost exceeds the marginal benefit of the drug, theoretically causing a welfare loss to society because these resources could have been better employed elsewhere (Pauly 1968). The premise behind cost sharing is that when patients face out-of-pocket payments for health care, they think more carefully about their consumption and reduce this unnecessary demand. Another objective of user changes is to raise revenue for the health care system. By forcing patients to face some out-of-pocket costs, an insurer can shift the saved funds to other more cost-effective areas of the health care system.

While a number of studies have calculated the elasticity of demand for prescription drugs, it is unclear whether the elasticity has changed over time such that previous estimates are outdated. The RAND study overcame many methodological problems that current studies often face, but it has been 25 years since this experiment was implemented. More recent elasticity estimates exist for Canada and the Netherlands, but there is still uncertainty as to whether consumers in these countries react differently to price changes than Americans. As prescription drug expenditures have been rising rapidly in the US, third-party payers have increasingly applied cost sharing as a mechanism to contain expenditures, and the effect of this trend on drug consumption has important policy implications. Another issue is that no American studies have simultaneously accounted for

[1] A co-payment is a fixed payment per prescription, coinsurance is a payment that is a percentage of the cost of a prescription, and a deductible is an out-of-pocket amount the individual must spend for prescription drugs beyond which the third-party payer will cover some or all of the costs.

unobserved heterogeneity, sample selection, and an endogenous co-payment variable. The failure to account for these factors in non-experimental settings may have led to biased estimates.

The purpose of this paper is to offer an updated estimate of the elasticity of demand for prescription drugs using the 1996-2003 Medical Expenditure Panel Survey. We employ novel panel data techniques to account for heterogeneity, sample selection, and endogeneity. Section 2 offers an abbreviated review of the literature on cost sharing for prescription drugs, while Section 3 briefly discusses the American health care system. Section 4 presents the econometric model, Section 5 offers the findings from the descriptive statistics and the diagnostic tests, and Section 6 presents the results from the econometric analysis. Finally, Section 7 wraps up with a discussion of the results and the limitations.

2. Literature review

A number of papers have examined the link between cost sharing for prescription drugs and the demand for prescription drugs, specifically, the probability of obtaining at least one prescription medication, the number of drugs obtained, prescription drug expenditures, and the elasticity of demand. As our primary concern in this paper is the effect of user fees on the volume of medications obtained and the elasticity of demand, we will only discuss the literature which analysed these two outcome measures. Because the MEPS database is comprised of individual-level observations, less focus is given to studies that used aggregate datasets in this section.

The main studies that used aggregate datasets spanned Australia, Belgium, Canada, the Netherlands, Sweden, the United Kingdom, and the United States, and the typical regression techniques were: OLS, generalised least squares, cointegration, and autoregressive statistical models and techniques. Most studies found a negative relationship between cost sharing for prescription drugs and volume (Nelson et al., 1984; Van Doorslaer, 1984; Reeder and Nelson, 1985; Lavers, 1989; O'Brien, 1989; Carrin and Van Dael, 1991; Ryan and Birch, 1991; Starmans et al., 1994; Hughes and McGuire, 1995; Martin and McMillan, 1996; McManus et al., 1996; Blais et al., 1999; Blais et al., 2003), although a few investigations found that cost sharing had a negligible effect on demand, at least for certain subpopulations (Reeder and Nelson, 1985; Soumerai et al., 1987; Carrin and Van Dael, 1991; Blais et al., 2001; Ong et al., 2003). Of the papers that calculated the elasticity of demand for prescription drugs using aggregate data (Van Doorslaer, 1984; Lavers, 1989; O'Brien, 1989; Carrin and Van Dael, 1991; Ryan and Birch, 1991; Hughes and McGuire, 1995), most of the estimates were between –0.64 and –0.021. As the effects of other covariates on demand in the aggregated setting are not pertinent to our research, we will not discuss these findings.

Meanwhile, the literature that used non-aggregate data to examine cost sharing for prescription drugs and volume and elasticity of demand spanned Australia, Canada, the Netherlands, Russia, the United Kingdom, and the United States. The main regression techniques were: the two-part model developed by Duan et al. (1983), and OLS, Poisson, negative binomial, random effects, panel tobit, and instrumental variables regression techniques. Table 1 lists the findings related to the impact of the primary explanatory variables on the demand for prescription drugs.

Table 1. The effect of various explanatory variables on the volume of prescription drugs

Variable	Volume	Studies
Level of cost sharing	-	Liebowitz et al. (1985) [us, es]; Foxman et al. (1987) [us, es]; Cameron et al. (1988)[aus, os]; Smith and Watson (1990)[uk, os]; Smith (1993)[us, os]; Grootendorst et al. (1997)[ca, os]; Johnson et al. (1997)[us, ns]; Street et al. (1999)[ru, os]; Balkrishnan et al. (2001)[us, ns]; Rector et al. (2003)[us, os]; Klick and Stratmann (2005)[us, os]
Level of cost sharing	negligible	Pilote et al. (2002)[ca, ns]
Female	+	Foxman et al. (1987)[us, es]; Cameron et al. (1988)[aus, os]; Shih (1999)[us, os]; Klick and Stratmann (2005)[us, os]
Age	+	Cameron et al. (1988)[us, os]; Smith and Watson (1990)[uk, os]; Grootendorst et al. (1997)[ca, os]; Street et al. (1999)[ru, os]; Van Vliet et al. (1999)[ne, os]
Age	-	Coulson and Stuart (1995)[us, os]; Coulson et al. (1995)[us, os]; Shih (1999)[us, os]; Klick and Stratmann (2005)[us, os]
Race		
White	+	Shih (1999)[us, os]
Income	+	Van Vliet et al. (1999)[ne, os]
Income	-	Foxman et al. (1987)[us, es]; Smith and Watson (1990)[uk, os]; Coulson and Stuart (1995)[us, os]; Grootendorst et al. (1997)[ca, os]; Van Vliet et al. (1999)[ne, os]
Education	+	Shih (1999)[us, os]; Street et al. (1999)[ru, os]; Van Vliet (2001)[ne, os]
Household size	+	Grootendorst et al. (1997)[ca, os]
Household size	-	Street et al. (1999)[ru, os]
Poor health	+	Foxman et al. (1987)[us, es]; Cameron et al. (1988)[aus, os]; Smith and Watson (1990)[uk, os]; Coulson and Stuart (1995)[us, os]; Grootendorst et al. (1997)[ca, os]; Street et al. (1999)[ru, os]; Van Vliet et al. (1999)[ne, os]; Klick and Stratmann (2005)[us, os]

[au]Australia, [ca]Canada, [ne]The Netherlands, [ru]Russia, [uk]United Kingdom, [us]United States
[es]experimental study, [ns]natural study, [os]observational study

Most studies found that higher levels of drug cost sharing decreased demand, although Pilote et al. (2002) determined that cost sharing had little effect on volume. Although most papers found the expected relationship between income and demand, Van Vliet et al. (1999) established that income increased volume up to a certain point, beyond which there was a negative association between the two variables. Household size is one variable that may exhibit varying influences on volume. Specifically, households with young children, disabled or sick individuals, and elderly members will be more likely to consume more prescriptions, but larger households may struggle more financially, which could dampen the prescription drug volume. There were mixed results for this variable, Grootendorst et al. (1997) finding a positive relationship between household size and demand and Street et al. (1999) finding a negative relationship. These differences may have

occurred because of the settings, specifically, drug coverage in Canada is more generous than in Russia, and larger Canadian households may face less financial difficulty when household drug consumption is greater.

In terms of elasticity estimates, most ranged from –0.56 to –0.10 (Harris et al., 1990; Smith, 1990; Smith, 1993; Coulson and Stuart, 1995, Street et al., 1999; Klick and Stratmann, 2005), indicating that the demand for prescription drugs is relatively inelastic.

The literature review reveals that few papers have recently investigated the link between cost sharing for prescription drugs and demand and even fewer papers have recently calculated the elasticity of demand for prescription drugs. Only two papers (Grootendorst et al., 1997; Balkrishnan et al., 1997) used panel data, even though cross-sectional data may suffer from omitted variable bias. Another important issue is that many papers did not control for the endogeneity of the price variable, which may be a factor in the American setting where many individuals choose their insurance contracts

3. The American health care system

Insurance coverage in the US is fragmented with individuals receiving coverage from various private and public third-party payers and 16 percent of the population having no insurance coverage (US Census, 2005). With the exception of some public insurance programs, third-party payers heavily rely on cost sharing to limit moral hazard and constrain health care expenditures, particularly pharmaceutical expenditures. Although pharmaceutical expenditures comprised about 10 percent of total national health spending in 2004, prescription drugs contributed 14.7 percent of total health care spending growth from 1994-2004 (KFF, 2006).

Medicare, which insured around 40 million Americans in 2004, is a national public insurance program for individuals over the age of 65, some non-elderly persons with specific disabilities, and persons of all ages with End Stage Renal Disease (CMS, 2006). In terms of prescription drug coverage, Medicare Part B is a voluntary insurance program and covers outpatient and physician services and some medical services, including certain prescription drugs that cannot be self-administered. Since January 2006 Medicare Part D has offered outpatient prescription drug coverage, although other entities (such as private companies or public groups) actually provide the coverage.

The Medicaid program, which covered approximately 37 million people in 2004, is intended to cover low-income individuals and families. However, as Medicaid is administered at the state level, each state establishes its own eligibility requirements (CMS, 2006). States have considerable freedom in determining eligibility for coverage, although there are certain groups that states must cover in order to receive Federal funds. All states offer prescription drug coverage, although the medications covered, coverage restrictions such as prescription limits, formularies, co-payments (which cannot exceed $3 per prescription), and other prescription control measures differ by state (CMS, 2006). States have increasingly been employing these drug cost containment tools as growth in prescription drug expenditures has outstripped growth in other areas of health care expenditure (KFF, 2002).

Private employer-sponsored insurance is the primary source of coverage for 60 percent of the population (US Census, 2005), as there are tax incentives for employers that offer health insurance. For those who cannot obtain employer-sponsored coverage, non-group health insurance is an option. Private insurance companies have been increasing user fees for prescription drugs significantly within the past few years, although the growth rate in out-of-pocket costs for non-preferred prescriptions has been higher than the growth rates for generic and preferred prescriptions (KFF/HRET, 2005).

4. The model

We model the number of prescription drugs that the individual obtains in a given year as a function of the out-of-pocket price of prescription medications and selected demographic, socioeconomic, and health characteristics. Whether the individual obtains any prescriptions is based on marginal cost – marginal benefit comparison that he makes when faced with the decision on whether to obtain a prescription. If the individual determines that the marginal cost of obtaining a prescription is always greater than the marginal benefit in a given period, then he foregoes any consumption. Because we are unable to observe whether a value of zero for the number of prescriptions obtained is due to the individual never needing a prescription (not a true zero) or the individual obtaining a prescription and choosing not to purchase it (a true zero), we employ sample selection techniques. A second important issue is that the co-payment may be endogenous, as the number of prescriptions the individual consumed in the previous period may influence his choice of a co-payment level. That is, individuals who consume more prescriptions in the previous period may seek lower cost sharing arrangements in the next period to offset the cost of their medications.

Because MEPS contains two years of data for selected individuals, we use unbalanced panel data techniques. Intuitively, we chose a fixed effects framework because unmeasured individual-specific effects, such as preferences for prescription drugs and access to medical care, may affect the demand for prescription drugs. This assumption is formally tested, and we present the results of this specification test in the next section.

The model detailed here was developed by Semykina and Wooldridge (2005) and consists of three main equations:

(1) $y_{it} = g_i + x_{it}\beta + c_{it}\delta + u_{it}$ $\quad y_{it} = y_{it}^{*}$ for $b_{it} = 1$

y_{it} is not observed for $b_{it} = 0$

(2) $c_{it} = \theta_i + z_{it}\alpha + y_{it}\gamma + v_{it}$ $\quad c_{it} = c_{it}^{*}$ for $b_{it} = 1$

c_{it} is not observed for $b_{it} = 0$

(3) $b_{it} = 1[\eta_i + z_{it}\gamma + \varepsilon_{it} > 0]$ $\quad$ for $t = 1,...,T$.

The variables from equation (3) represent the following: y_{it} is the number of prescription drugs obtained, x_{it} are the explanatory variables that determine y_{it}, c_{it} is the endogeneous co-payment variable, β and δ are the coefficients on x_{it} and c_{it}, g_i is the individual-specific term, and u_{it} is the error term. In the second equation which determines the co-payment level, z_{it} are the instruments, which are strictly exogenous conditional on g_{it}, while θ_i is the individual-specific term, and v_{it} is the error term. Finally, b_{it} is a sample selection indicator for both y_{it} and c_{it}, and η_i is the individual-specific term and ε_{it} is the error term. We assume that $\varepsilon_{it}|z_i, \eta_i \sim$ Normal(0,1), allowing b_{it} to be estimated through an unobserved effects probit model.

The Semykina and Wooldridge (2005) estimator further models the relationship between the individual-specific effect (η_i) and the instrumental variables (z_i). The chosen method is based on Mundlak (1978) and models the unobserved effect as:

(4) $\eta_i = \tau + \bar{z}_i\xi + a_i$.

Substituting (4) into (3), the selection indicator becomes:

(5) $b_{it} = 1[\tau_2 + z_{it}\gamma + \bar{z}_i\xi_2 + \varpi_{it} > 0]$ $\quad$ for $t = 1,...,T$,

where $\varpi_{it}|z_i \sim$ Normal(0,1).

If we also assume that $u_{it} = \tau_1 + \bar{z}_i\xi_1 + a_{i1}$ where $E(a_{i1}|z_i, \varpi_{it}) = E(a_{i1}|\varpi_{it}) = \phi_{t1}\varpi_{it}$, then we can substitute equation (5) into the main equation (1), with the result:

(6) $y_{it} = x_{it}\beta + \tau_1 + \overline{z}_i\xi_1 + a_{i1} + u_{it} = x_{it}\beta + \tau_1 + \overline{z}_i\xi_1 + \psi_{it}$,

where $\psi_{it} = a_{i1} + u_{it}$. Further assuming that $E(u_{it}|z_i, \varpi_{it}) = E(u_{it}|\varpi_{it}) = \rho_t\varpi_{it}$, we determine that:

(7) $E(\psi_{it}|z_i, \varpi_{it}) = E(a_{i1}|z_i, \varpi_{it}) + E(u_{it}|z_i, \varpi_{it}) = \phi_t\varpi_{it} + \rho_t\varpi_{it} = \kappa_t\varpi_{it}$,

and substituting this into (6) results in:

(8) $y_{it} = x_{it}\beta + \tau_1 + \overline{z}_i\xi_1 + \kappa_t E(\varpi_{it}|z_i, b_{it}) + e_{it}$.

The model is made robust to heteroskedasticity by using the White (1980) estimates of variance, which are available in STATA 9 through the *robust* command.

To determine whether this procedure is merited for the given sample, Semykina and Wooldridge (2005) developed a test, which involves first estimating a probit model of this equation for each time period:

(9) $P(b_{it} = 1|z_i) = \Phi(\tau_2 + z_{it}\gamma + \overline{z}_i\xi_2)$.

Then, we use the results of each probit to calculate the inverse Mills ratios, λ_{it}, as given by the formula in the section on sample selection. For the sample where $b_{it} = 1$, we use fixed effects two-stage least squares to estimate the equation:

(10) $y_{it} = g_i + x_{it}\beta + c_{it}\delta + \rho\lambda_{it} + u_{it}$,

and if the coefficient for λ_{it} is significant, we reject the null hypothesis of no selection bias. Note that we can also interact the inverse Mills ratio with the time dummies, and using a robust variance matrix, test the joint significant of all of those terms with a Wald test.

An alternative to the Heckman methodology is the two-part model developed by Duan et al (1983). There has been extensive debate in the literature regarding the choice between the two-part model and the sample selection model (Jones 2001). One argument has been that two-part models are more appropriate for sequential decisions, although Maddala (1985) argues that even when decisions are sequential, the decisions will be correlated if there are omitted variables common to both. Leung and Yu (1996) determined that the sample selection model performs poorly when there is collinearity, which can arise in certain contexts: when there is a large degree of censoring, when there are few exclusion restrictions, when there is little variability between regressors, or when there are weak instruments (Leung and Yu 1996). In the absence of collinearity, which can be verified using the condition number or the variance inflation factor, the t-test on the inverse Mills ratio is an indicator of which two specifications is more appropriate.

5. Descriptive statistics and results of diagnostic tests

This section of the paper discusses the dataset used for the analysis, the results of the descriptive statistics, and the specification tests for the econometric model.

We employ the 1996-2003 Medical Expenditure Panel Survey (MEPS)[2] for our analysis (AHRQ 2004). One of the main reasons we chose this time period is pragmatic: 1996 to 2003 are all of the years available in the MEPS database. It was also a period of change for the US as a recession started in 2000 and appears to have lasted until 2002 (Davis, 2005), an event that likely had an impact on insurance coverage and prescription drug consumption. MEPS is a nationally representative sample of the U.S. civilian, non-institutionalized population with over sampling of Hispanics and blacks. It is an overlapping panel in which five in-person interviews are collected over a two-year calendar period using computer-assisted personal interviewing (CAPI) technology. The survey collects data from a new sample of households each subsequent year, allowing for overlapping panels of survey data and longitudinal analysis. The raw data consisted of 237,874 observations, and after removing individuals under the age of 18 (69,640 observations) and excluding observations with missing data (5,169 observations), our final sample consisted of 163,065 individuals.

The creation of the MEPS dataset and subsequent analysis was carried out in STATA 9.0. For some of the panel data analysis, the STATA *xt* commands, which account for unbalanced panels, were employed. We also used the *regress* command along with time averages for each explanatory variable for the Semykina and Wooldridge (2005) estimator; the variances for this model were also adjusted to account for sample selection and endogeneity according to Semykina and Wooldridge (2005).

We chose to exclude individuals under the age of 18 because children generally do not choose their health insurance coverage or the number and types of drugs to consume. These decisions are many taken by their guardians instead. In terms of the descriptive statistics, Table 2 lists the possible explanatory variables along with their means and standard deviations.

Various trends appear when we examine the summary statistics. The co-payment bands were set at the 25^{th}, 50^{th}, and 75^{th} percentiles for individuals with positive prescriptions, as the co-payment is not observed for those who do not consume any prescriptions in a given year. The descriptive statistics reveal that approximately half of the sample has a co-payment of less than $6.82 (in 1996

[2] An advantage of this dataset is that no other studies have used MEPS to examine the impact of cost sharing on prescription drug utilization

dollars), although this percent is relatively large because it includes the sample that did not consume any drugs. The percent of the sample was split relatively evenly between the other co-payment bands. Most of the adult sample is between the ages of 18 and 65, while the gender variables indicate that females make up a slightly larger proportion of the sample. Slightly more than half of the sample is white, while blacks and Hispanics make up almost 40 percent of the sample. Because of the study design where blacks and Hispanics were oversampled, this proportion is higher than the national average.

Table 2. Percent of sample exhibiting specific characteristics: 1996-2003

Variable	Adult sample (N = 163,065)
RX co-payment, <=$6.82	51.01
RX co-payment, $6.83 – $12.63	16.39
RX co-payment, $12.64 – $24.19	16.30
RX co-payment, >$24.19	16.30
Age, <=30	24.99
Age, 31 - 45	31.34
Age, 45 - 65	27.94
Age, 65 – 74	8.64
Age, >74	7.08
Male	46.22
Female	53.78
White	60.96
Black	13.57
Hispanic	21.27
Other race/ethnicity	4.20
Income, <=7955	25.08
Income, 7966 – 15910	27.01
Income, 15911 – 23865	17.52
Income, 23866 – 31820	10.60
Income, >31820	19.79
Married	56.86
Not married	43.14
Good health	85.50
Poor health	14.50
Diagnosed with a major disease	17.57
Not diagnosed with a major disease	82.43
Has a limitation to activities of daily living	2.15
Does not have a limitation to activities of daily living	97.85

The income bands were created using the Federal Poverty Level, where each band represents an increase in income to *n*th percent of the FPL (100%, 200%, 300%, 400%), and this variable indicates that a disproportionate part of the adult sample has very low income. In terms of health status and health care use variables, most of the sample reported being in good health. Only about 18 percent of the adult sample had been diagnosed with one of the leading causes of death (asthma, coronary heart disease, stroke, chronic obstructive pulmonary disease, malignant cancer, and diabetes (CDC, 2006)). Finally, only about 2 percent of the sample faced at least one limitation to an activity of daily living.

Before discussing the results of the model, it is important that we consider the results of the specification tests for the appropriateness of various assumptions. We employed specific tests for

the specification of the model, the assumption of an endogenous co-payment, and the choice of main variables and instruments (Table 3).

Table 3. Results from various specification tests

Test	Models compared	Results
F-test for appropriateness of fixed effects	OLS and FE-OLS	F(38891, 38883) = 5.21 (p=0.000)
Hausman specification test for random effects	FE-OLS and RE-OLS	$\chi^2(8) = 3099$ (p=0.000)
Alternative to Hausman specification test for random effects	FE-OLS and RE-OLS	$\chi^2(1) = 51 - 2564$ (p=0.000)
Durbin-Wu-Hausman test for endogeneity	FE-OLS and FE-2SLS	t = 9.28 (p=0.000)
Semykina -Wooldridge test (Wald test) for sample selection	FE-2SLS (no sample selection) and FE-2SLS (sample selection)	$\chi^2(8) = 277$ (p=0.000)
Condition index to test for multicollinearity		CI = 17.5
Variance Inflation Factor to test for multicollinearity		VIF = 6.74

Because of the panel nature of our data, we first tested for the appropriateness of a fixed effects model as compared to pooled OLS. The null hypothesis of the test is that all individual-specific parameters except for one are zero, i.e. $g_1 = ... = g_{n-1} = 0$. The F-statistic from this test indicated that we could reject the null hypothesis and conclude that a fixed effects model is more appropriate than pooled OLS. Although this test specified that a panel data model was more appropriate than pooled OLS, the question still remained as to whether a fixed effects or random effects framework should be used. The results of a Hausman test allowed us to reject this null hypothesis that a random effects model performs better than a fixed effects model. However, the Hausman test does not distinguish between misspecification of the model and the lack of correlation between the individual-specific error term and the explanatory variables in the model. Another way to test the appropriateness of the random effects model against the fixed effects model is to consider the fact that random effects constrains the within- and between-effects to be the same. This test is performed by decomposing each explanatory variable into its within- and between-effects, running a random effects regression, and testing whether the decomposed effects are equal. The results of this test are listed as an alternative to the Hausman test in Table 3 and indicate that we can reject the null hypothesis that the within- and between-effects are equal.

Next, we used a Durbin-Wu-Hausman test to examine the null hypothesis that the co-payment was exogenous to the model. An important note is that because there is potentially correlation between

the individual-specific effects and some of the explanatory variables, we used a fixed effects estimator for this test as it would be impossible to disentangle the endogeneity bias from omitted variable bias with the random effects and pooled OLS estimators. The statistic reported in the table is the t-statistic from the error term on the estimated co-payment variable, and the results of this test indicate that the co-payment variable is endogenous. However, the problem with this test is that it does not distinguish between endogeneity due to the endogenous co-payment variable and endogeneity due to sample selection. If we fail to reject the null hypothesis of no sample selection, then the Durbin-Wu-Hausman test is valid for testing endogeneity of the co-payment. As no test yet exists to distinguish between these two possibilities, we choose to treat the co-payment as endogenous.

In terms of sample selection, we tested for the existence of this problem using a Wald test proposed by Semykina and Wooldridge (2005). The null hypothesis of the test is that the explanatory variables are not correlated with the error term in the main equation, and the reported values in Table 3 indicate that sample selection is a problem. Moreover, when we adjust for serial correlation, the joint Wald test on all of the Mills ratio terms further confirms this result.

A problem that sometimes occurs with sample selection adjustments is multicollinearity, and to test for this problem, we use a condition index. A condition index of 20 or greater points to a possible multicollinearity problem (Greene, 2003). For all specifications, the condition index was less than 20, indicating that multicollinearity is not a significant problem. A second test is the Variance Inflation Factor (VIF), which indicates that multicollinearity is an issue for VIF values greater than 10. The mean VIF for each specification was less than 10, and again we concluded that multicollinearity was not a significant issue.

6. Results of the regression analysis

For the regression analysis, we transformed some of the variables, particularly total prescription drugs obtained, prescription drug expenditures, the prescription drug co-payment, and income per person in each family, into logarithms because these variables were highly skewed to the left. As we determined that the fixed effects estimator performed better than pooled OLS, we were unable to include variables that did not change over time in the estimation, including gender and race/ethnicity. Most variables that we hypothesized would significantly predict the demand for prescription drugs had little effect in the fixed effects framework, likely because omitted variables, such as preferences for prescription drugs and access to pharmacies, were capturing much of the impact on the demand for prescription drugs. We also examined a number of interaction effects, for

instance age and income, age and morbidity, and morbidity and self-reported health status, but none of these interactions were significant. The instruments were the main regressors along with whether the individual had non-Medicare public insurance coverage and whether the individual switched insurance coverage at least once during the year[3]. The public insurance variable was intended to control for the effect of different prescription drug prices as public insurance agencies tend to get the highest discounts for prescription drugs and can pass these savings along to patients in the form of lower co-payments. As for the change in insurance variable, individuals that switch insurance plans are likely to experience a change in their out-of-pocket requirements.

In order to obtain a general elasticity measure for the broad population, we estimated the effect of a change in the co-payment on the number of prescription drugs obtained in a year for the adult sample. The results of this estimation are available in Table 4.

Table 4. Estimates for the log of total number of prescription drugs obtained equation among adults[a,b,c]

Explanatory variable	Pooled OLS	Pooled 2SLS	Fixed Effects	Fixed Effects 2SLS	SS Fixed Effects 2SLS
(log) drug co-payment	0.063***	-0.423***	0.037***	-0.285***	-0.234***
	(0.004)	(0.020)	(0.004)	(0.074)	(0.062)
age between 30 and 39	0.204***	0.222***	-0.022	-0.031	-0.045
	(0.011)	(0.013)	(0.035)	(0.042)	(0.038)
age between 40 and 49	0.457***	0.507***	0.011	0.022	-0.021
	(0.011)	(0.012)	(0.044)	(0.050)	(0.048)
age between 50 and 64	0.741***	0.822***	0.092	0.105**	0.030
	(0.010)	(0.012)	(0.051)	(0.053)	(0.055)
age between 65 and 74	0.870***	1.047***	0.134**	0.152**	0.037
	(0.012)	(0.015)	(0.059)	(0.068)	(0.063)
age above 74	0.929***	1.131***	0.104	0.118	-0.034
	(0.013)	(0.016)	(0.068)	(0.072)	(0.072)
(log) income per person in family	0.023***	0.030***	0.003	0.001	0.001
	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)
individual reports poor health	0.553***	0.521***	0.058***	0.061***	0.058***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
individual diagnosed with at least one of leading causes of death	0.513***	0.534***	0.214***	0.226***	0.190***
	(0.008)	(0.008)	(0.013)	(0.014)	(0.019)
constant	1.239***	2.296***	2.205***	2.948***	1.845***
	(0.016)	(0.047)	(0.042)	(0.172)	(0.136)
N	77784	77784	77784	77784	77784
R^2	0.295	0.298	0.234	0.237	0.129

[a]standard errors in parentheses
[b]excluded dummy variables are age less than 30, individual reports being in good health, individual has not been diagnosed with at least of the leading causes of death
*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level

We conducted an F-test on the set of instruments, as discussed in Staiger and Stock (1997), to examine the null hypothesis that the instrumental variables were not significantly correlated with the endogenous variable. A rule of thumb is that the F-test on all the instruments needs to exceed 10,

[3] This variable indicated whether the individual changed between any of these insurance types at least one time in a given year: Medicare, Medicaid, Tricare, other state insurance programs, other public insurance programs, employer union insurance, other group insurance, self-employment insurance, non-group insurance, or private insurance (source unknown).

and our F-value of 48.35 was sufficient to determine that we did not have weak instruments. We also performed a Sargon test for over-identifying restrictions to determine whether the instruments were independent of the error term in the main equation. A statistically significant test statistic indicates that the instrument set is not independent of the error term, but as the value of our statistic from this test was 3.44 (p=0.063), we failed to reject the null hypothesis at $\chi^2(1)$.

The coefficients on all the variables were larger in the pooled setting, implying that the included variables were capturing the effects of individual-specific effects that were not included in the regression. The coefficient on the prescription drug co-payment variable was positive for the regressions where the endogeneity of the co-payment was not considered and negative in the models where we corrected for endogeneity. The positive coefficient on the co-payment in some of the regression could be explained by the existence of omitted variables (Angrist and Krueger, 2001). As a result, the residuals on the co-payment variable, which have essentially been removed in the endogeneity correction, were likely biasing the coefficient on the co-payment variable upwards. In the fixed effects model that accounted for endogeneity and sample selection, the elasticity of demand was –0.234 (p=0.000). In general, the coefficients on the age variable were positive for higher ages, indicating that prescription drug consumption increases with age. However, the coefficients were significant in the pooled regression setting and sometimes significant in the panel data models, potentially because the age variables were capturing unobserved effects in the pooled models. In fact, age appears to work partially through the initial decision to consume at least of prescription and partially through the determination of the co-payment, at least for higher age levels. While the income variable was significant in the pooled models and never significant in the panel data models, the coefficient on this variable was positive across all specifications. Income was probably capturing the effects of other unobserved variables, such as wealth, though. Both of the included health variables were almost always significant and positive, indicating that deteriorating health has an important effect on prescription drug consumption.

7. Discussion

This section of the paper discusses the results from the econometric analysis. One interesting phenomenon was that there was a positive association between the out-of-pocket cost and the demand for prescription drugs in the raw data. As this is the opposite of what we would expect, we hypothesized that other factors which determine the co-payment, particularly the structure of insurance in the United States, were influencing this result. Based on this hypothesis, we empirically examined whether the co-payment was endogenous and confirmed that we needed to correct for this bias. Additionally, the fixed effects framework was more efficient than pooled OLS,

implying that a number of individual-specific factors, such as preferences for prescription drugs, unobserved wealth, and access to health care, are important predictors of the demand for prescription drugs. As the coefficients on all the explanatory variables decreased when the fixed effects framework was used, this indicates that at least some coefficients estimates from the literature may be larger than if the authors had accounted for unobserved individual-specific effects.

Nonetheless, our elasticity estimate of –0.234 is in line with the estimates from the literature, which generally ranged from –0.56 to –0.10 with non-aggregate data. Estimates of the elasticity of demand for medical care from the RAND study ranged from –0.20 to –0.10 (Manning et al., 1981; Manning et al., 1987) and are thus very close to the estimate from this study. There are a number of reasons why our estimate might differ from those found in the literature, though. The higher elasticity estimates from other studies in the literature may have been caused by omitted variable bias in studies that did not use panel data techniques and a failure to account for the endogeneity of the co-payment in some studies. Furthermore, authors that analysed datasets from outside the United States may have obtained different results as other developed countries have universal health insurance systems, and individuals in these countries may face less uncertainty related to future changes in their out-of-pocket costs.

A value of –0.234 is relatively inelastic, indicating that consumers are not particularly sensitive to changes in the prices of out-of-pocket prescription drugs. This may be caused by a lack of good substitutes for prescription drugs in certain situations; for example, individuals who use statins may be able to forego difficult surgeries such as a coronary artery bypass grafts or an angioplasty. Even diet and exercise are not perfect substitutes for prescription drugs, as these alternatives can only improve health to some extent.

In terms of the other variables that we used to predict the demand for prescription drugs, age always significant in the pooled setting and sometimes significant in the fixed effects framework. Specifically, the variable representing the individual being between the ages of 65 and 74 had a positive coefficient in the regression for total drugs consumed. The variable also tended to be positive as age increased and was decreasing at very high ages. As for the income variable, this was never significant in the fixed effects models, likely because wealth is a better predictor of drug consumption. Additionally, other variables such as health status may be picking up the income effects, as there is generally a positive correlation between income and health (Macinko et al., 2003).

All of the health status variables were significant and positive, and it is not surprising that individuals who are perceived to be in poorer health would be more likely to seek medical care. Also, those who suffer from the specific diseases that are the leading causes of death in the United States are more likely to need prescription drugs. This observation is in line with the findings from the literature on cost sharing for prescription drugs.

There are a number of limitations that should be highlighted. Although the dependent variable representing the number of prescriptions obtained by the individual was a count variable, we were unable to use count variable techniques for this analysis because truncated panel data models are not yet available. Our analysis instead assumed that the individual could theoretically consume an infinite number of prescriptions. Future research should incorporate these techniques into the analysis to determine if the outcomes differ. A second issue is our inability to measure whether respondents complied with their therapies. For example, although the doctor may have written a prescription for two weeks of painkillers, the patient may have only filled one week's worth of medicine and proceeded to cut his pills in half or skip pills. In these situations, we are unable to measure whether user fees changed the individual's behaviour.

Another question that remains is whether cost sharing led to a decrease in the use of inappropriate medications, appropriate medications, or both in the studied population. If higher user fees cause individuals to decrease their consumption of inappropriate medications or medications where the marginal cost outweighs the marginal benefit, then there is a welfare gain. However, if cost sharing leads to a decrease in both appropriate and inappropriate medications, the net benefit may be a welfare gain or loss, depending on the magnitude of change for each type of medication.

A third limitation is our inability to measure adverse selection because MEPS does not contains information on premium payments. Economic theory indicates that adverse selection will occur in a private insurance market, and testing for the existence of this phenomenon would offer insights into arguments regarding universal insurance coverage and a national insurance program in the United States.

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Appendix

Appendix Table 1. Probit estimates for first stage of FE-2SLS procedure predicting probability of prescription drug use[a,b,c]

Explanatory variable	1996	1997	1998	1999	2000	2001	2002	2003
age 30 to 39	-0.342**	0.233*	-0.484***	-0.031	-0.259*	-0.262**	-0.025	-0.168
	(0.161)	(0.122)	(0.147)	(0.138)	(0.139)	(0.128)	(0.118)	(0.182)
age 40 to 49	-0.502**	-0.049	-0.560***	0.333	-0.337*	-0.486***	-0.078	-0.275
	(0.226)	(0.169)	(0.204)	(0.195)	(0.191)	(0.175)	(0.161)	(0.247)
age 50 to 64	-0.384	-0.073	-0.684***	0.403	-0.549**	-0.151	-0.184	-0.431
	(0.284)	(0.214)	(0.257)	(0.253)	(0.249)	(0.225)	(0.207)	(0.315)
age 65 to 74	-0.075	0.117	-0.724**	0.225	-0.172	-0.349	-0.060	0.158
	(0.392)	(0.299)	(0.365)	(0.356)	(0.347)	(0.311)	(0.296)	(0.484)
age greater than 74	0.690	0.152	-0.775	-0.007	-0.451	-0.837	0.053	0.396
	(0.513)	(0.410)	(0.492)	(0.473)	(0.484)	(0.449)	(0.418)	(0.726)
(log) income per person in family	0.050***	-0.001	0.019	0.005	0.022	0.006	-0.023*	-0.003
	(0.016)	(0.012)	(0.016)	(0.016)	(0.015)	(0.013)	(0.013)	(0.019)
poor health	0.164**	0.208***	-0.091	0.156	0.108	0.125**	0.122**	0.167**
	(0.076)	(0.059)	(0.072)	(0.075)	(0.073)	(0.063)	(0.057)	(0.084)
diagnosis of at least one of leading causes of death	0.386**	0.587***	0.482***	0.866***	0.677***	0.711***	0.664***	0.693***
	(0.111)	(0.088)	(0.104)	(0.101)	(0.101)	(0.087)	(0.085)	(0.135)
has public insurance (non Medicare)	0.522***	0.380***	0.161	0.225**	0.430***	0.259***	0.359***	0.202
	(0.122)	(0.093)	(0.112)	(0.115)	(0.109)	(0.092)	(0.086)	(0.127)
changed insurance coverage this year	-0.150***	-0.014	-0.045	-0.092*	-0.055	-0.079*	-0.054	-0.087
	(0.053)	(0.041)	(0.050)	(0.049)	(0.048)	(0.041)	(0.038)	(0.059)
(mean) age 30 to 39	0.521***	-0.043	0.672***	0.276*	0.500***	0.471***	0.249**	0.374**
	(0.164)	(0.125)	(0.150)	(0.141)	(0.143)	(0.131)	(0.121)	(0.184)
(mean) age 40 to 49	0.723***	0.368**	0.920***	0.001	0.641***	0.803***	0.417**	0.650***
	(0.228)	(0.172)	(0.206)	(0.198)	(0.194)	(0.178)	(0.163)	(0.249)
(mean) age 50 to 64	0.858***	0.602***	1.206***	0.139	1.119***	0.684***	0.782***	1.036***
	(0.286)	(0.216)	(0.260)	(0.255)	(0.252)	(0.226)	(0.209)	(0.317)
(mean) age 65 to 74	0.878**	0.675**	1.509***	0.690	1.068***	1.161***	1.044***	0.777
	(0.391)	(0.302)	(0.370)	(0.358)	(0.351)	(0.313)	(0.300)	(0.489)
(mean) age greater than 74	0.055	0.683	1.709***	0.945**	1.438***	1.873***	0.989**	0.779
	(0.511)	(0.414)	(0.495)	(0.477)	(0.489)	(0.451)	(0.422)	(0.732)
(mean) (log) income per person in family	-0.018	0.036***	0.026	0.040**	0.024	0.041***	0.073***	0.062***
	(0.016)	(0.013)	(0.016)	(0.016)	(0.016)	(0.014)	(0.013)	(0.020)
(mean) poor health	0.434***	0.486***	0.806***	0.486***	0.590***	0.483***	0.504***	0.299***
	(0.090)	(0.068)	(0.086)	(0.087)	(0.086)	(0.073)	(0.068)	(0.089)
(mean) diagnosis of at least one of leading causes of death	0.726***	0.501***	0.591***	0.245**	0.479***	0.489***	0.552***	0.387***
	(0.115)	(0.093)	(0.111)	(0.105)	(0.107)	(0.091)	(0.090)	(0.140)
(mean) has public insurance (non Medicare)	-0.307**	-0.118	0.172	0.154	-0.054	0.101	-0.034	0.204
	(0.129)	(0.097)	(0.119)	(0.121)	(0.114)	(0.097)	(0.091)	(0.130)
(mean) changed insurance coverage this year	0.065***	-0.067	-0.081	-0.095	-0.121**	-0.107**	-0.132***	-0.085
	(0.067)	(0.051)	(0.063)	(0.063)	(0.060)	(0.053)	(0.048)	(0.064)
constant	-0.202	-0.348***	-0.380***	-0.362***	-0.373***	-0.329***	-0.413***	-0.455***
	(0.032)	(0.026)	(0.031)	(0.030)	(0.030)	(0.026)	(0.024)	(0.025)
N	15560	23456	16198	16901	17354	23361	26964	23271
Log-likelihood	-8741	-13250	-9008	-9443	-9608	-12714	-14608	-12726
probability > χ^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

[a]standard errors in parentheses

[b]excluded dummy variables are age less than 30, individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death

[c]the mean variables are calculated by taking the time mean of each variable for each individual in the sample

*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level

Appendix Table 2. Estimates for the log of the prescription drug co-payment and the log of the number of drugs consumed[a,b]

Explanatory variable	drug co-payment	number drugs consumed
(log) drug co-payment		-0.234*** (0.062)
age between 30 and 39	0.005 (0.048)	-0.045 (0.037)
age between 40 and 49	0.087 (0.061)	-0.021 (0.048)
age between 50 and 64	0.109 (0.071)	0.029 (0.054)
age between 65 and 74	0.101 (0.082)	0.036 (0.063)
age above 74	0.114 (0.094)	-0.034 (0.071)
(log) income per person in family	-0.004 (0.004)	0.000 (0.002)
individual reports poor health	-0.004 (0.013)	0.057*** (0.010)
individual diagnosed with at least one of leading causes of death	-0.001 (0.011)	0.19*** (0.018)
has public insurance (non Medicare)	-0.513*** (0.029)	
changed insurance coverage this year	0.095*** (0.013)	
year is 1997	0.132*** (0.021)	0.081*** (0.020)
year is 1998	0.178*** (0.026)	0.145*** (0.030)
year is 1999	0.212*** (0.026)	0.191*** (0.032)
year is 2000	0.29*** (0.025)	0.213*** (0.034)
year is 2001	0.324*** (0.024)	0.311*** (0.034)
year is 2002	0.321*** (0.023)	0.369*** (0.033)
year is 2003	0.408*** (0.028)	0.411*** (0.038)
lambda	-0.229*** (0.051)	0.089 (0.066)
lambda * 1997	-0.022*** (0.042)	-0.124*** (0.035)
lambda * 1998	-0.007*** (0.049)	-0.163*** (0.051)
lambda * 1999	-0.047*** (0.049)	-0.200*** (0.051)
lambda * 2000	-0.131*** (0.049)	-0.175*** (0.052)
lambda * 2001	-0.064*** (0.046)	-0.202*** (0.048)
lambda * 2002	-0.052*** (0.044)	-0.259*** (0.046)
lambda * 2003	0.148*** (0.054)	-0.227*** (0.054)
(mean) age 30 to 39	-0.039 (0.051)	0.248*** (0.042)
(mean) age 40 to 49	-0.087 (0.064)	0.481*** (0.052)
(mean) age 50 to 64	-0.056 (0.074)	0.711*** (0.060)
(mean) age 65 to 74	0.126 (0.086)	0.871*** (0.074)
(mean) age greater than 74	0.188* (0.098)	0.999*** (0.083)
(mean) (log) income per person in family	0.008 (0.004)	0.027*** (0.003)
(mean) poor health	0.061*** (0.019)	0.592*** (0.018)
(mean) diagnosis of at least one of leading causes of death	-0.015 (0.021)	0.312*** (0.019)
(mean) has public insurance (non Medicare)	-0.38*** (0.031)	0.047 (0.032)
(mean) changed insurance coverage this year	0.282*** (0.011)	-0.072 (0.020)
constant	2.495*** (0.048)	1.845*** (0.135)
N		
R^2		

[a]standard errors in parentheses

[b]excluded dummy variables are age less than 75, (age less than 85 for revised elderly regression), (individual is not retired for revised elderly regression), individual reports being in good health, individual has not been diagnosed with at least one of the leading causes of death, (individual does not report at least one limitation to activity of daily living for revised elderly regression)