

How Sensitive are Seniors to the Price of Prescription Drugs?

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Abstract

This study estimates the demand curve for prescription drugs among elderly Medicare beneficiaries. In contrast to previous work, the current analysis uses a measure of price rather than insurance status as the key explanatory variable to test for seniors' sensitivity to prescription drug price changes. The instrumental variable estimates show that a one percentage point increase in the coinsurance rate implies a 0.97 percent decrease in the number of prescriptions filled and a 0.91 percent decrease in total drug expenditures. This finding indicates that seniors are far more responsive to prescription drug price changes than suggested by studies that examine younger individuals.

I. Introduction

The current Medicare policy debate centers around adding prescription drug coverage to the Medicare benefits package. However, estimates of the cost of such a program vary greatly, depending on both the generosity of the benefit and the underlying actuarial assumptions (Gluck, 1999). Probably the most substantive, and least researched, of these assumptions concern how seniors will change their behavior when prescription drug insurance is implemented. That is, will prescription drug coverage under Medicare, which implies a lowering of the price of prescription drugs, lead to a small or a large increase in the quantity of prescription drugs demanded?

In this paper we estimate the sensitivity of the elderly to changes in the price of prescription drugs. We use observed variation in the coinsurance rates faced by elderly individuals, which is due to differences in their insurance coverage. While previous studies have estimated the effect of whether a senior has insurance on the use of prescription drug consumption, we estimate a demand curve for prescription drugs. We regress drug demand measures on individual coinsurance rates and other explanatory variables. This allows us to examine how prescription drug demand varies with the effective price, rather than treating each insurance option as a dummy variable.

The change in behavior in response to the presence of insurance is known as moral hazard. However, identification of moral hazard effects is complicated by the fact that individuals are not randomly assigned to supplemental drug coverage insurance plans, but instead self-select the coverage status that best meets their needs. Economic research over the past two decades has consistently shown that self-selection into insurance plans must be addressed in empirical research that attempts to quantify the moral hazard effect (Atherly 2001). Self-selection implies that the price in the prescription drug demand equation is endogenous. We estimate our model using instrumental variables, which allows us to control for the endogeneity of the prescription drug price (i.e. the individual coinsurance rate). Using this method we identify the effects of prescription drug prices on consumption, while controlling for unobserved self-selection effects.

The federal Medicare program insures the vast majority (more than 95 percent) of elderly (age 65+) adults in America. While it does not cover prescription drugs, seniors have several options for obtaining coverage for prescription drugs outside of traditional Medicare. Some seniors obtain health insurance that covers drugs through a former employer, and seniors with low income can obtain coverage through Medicaid. A third option is private insurance which comes in the form of supplemental health insurance policies (known as "Medigap"), and some of these policies provide additional coverage for prescription drugs. Finally, HMOs that specialize in serving Medicare beneficiaries offer Medicare + Choice plans which often include drug coverage.

We examine the behavior of subgroup of all elderly because this sub-sample allows us to employ instruments with which we can identify the demand curve for prescription drugs. Our sample includes seniors with Medigap and Medicare + Choice plans and excludes seniors with employer-sponsored insurance and seniors with Medicaid coverage. With our chosen sub-sample, we use state level instruments to control for the endogeneity of the price in the prescription drug demand equation.

Section II briefly reviews the how previous literature addresses the problem of disentangling the moral hazard from the self-selection effects. Section III describes the research design and describes various insurance options. Section IV introduces the econometric model, and Section IV describes the data sources. Results are discussed in Section VI and Section VII presents conclusions.

II. Previous literature

The findings in the current literature are based on experimental and non-experimental studies. These studies estimate the magnitude of the moral hazard effect, i.e. the change in drug consumption due to a change in the price of prescription drugs, and the adverse selection effect, i.e. the increase in drug consumption that is due to individuals' choosing an insurance plan that best suits their needs.

Experiments randomize individuals into treatment groups, thus allowing a measure of moral hazard that is unbiased by self-selection. In the 1980s RAND Health Insurance Experiment (HIE), scholars found that individuals with full coverage (no coinsurance) filled fifty percent more prescriptions than those with no coverage, although this effect may have been solely due to changes in the number of doctor visits (Newhouse, et. al. 1993). However, the HIE bears only limited relevance to the current policy debate because the experimental subjects were all non-elderly, and because drugs' share of total medical spending has increased greatly since the time of the experiment, suggesting a major shift in the basic structure of the demand for health care.

Studies using non-experimental methods include those of Smith and Kirking (1992), Ettner (1997), Coulson, et. al. (1995), Atherly (2002), Lillard, Rogowski, and Kington (1999).¹

Smith and Kirking (1992) review a number of studies of demand for drugs and find that estimates of price elasticity (for samples comprising the non-elderly or adults of all ages) range from -0.10 to -0.33. These estimates are drawn from quasi-experiments (rather than random experiments), but none of the reviewed studies have controlled for sample selection effects.

Ettner (1997) identifies the adverse selection and moral hazard effects of supplemental health insurance by assuming that employer-sponsored retiree insurance is exogenously given, while allowing for the potential endogeneity of self-purchased Medigap insurance. Using the 1991 Medicare Current Beneficiary Survey (MCBS), she compares differences in medical care expenditures between individuals with each type of private supplemental insurance (employer-sponsored and Medigap) and those with fee-for-service (FFS) Medicare only. She estimates that supplemental insurance (the coefficient on the employer insurance indicator) increases total health care expenditures between \$281 and \$760, depending on the comprehensiveness of coverage. She

¹ See U.S. Department of Health and Human Services (2000) and Levy (1992) for a recent review of the literature.

further estimates that adverse selection increases (the coefficient on the indicator for Medigap less the coefficient for employer-sponsored insurance) health care expenditures between \$446 and \$516.

Coulson, et al. (1995) formally test for self-selection into plans that cover prescription drugs. The data come from a mail survey of elderly Pennsylvania residents. Coulson et al. (1995) estimate a generalized two-stage sample selection model in which the first stage involves choosing among five levels of insurance coverage and the second stage involves choosing the amount of drugs to consume. The second stage regressors include a vector of health and demographic controls, dummy variables for coverage, and an inverse Mills ratio term to capture selection effects. The authors found that supplemental insurance for drugs (from any private source) increases the number of prescriptions filled by about 27 percent. They also found that seniors enrolled in Pharmaceutical Assistance Contract for the Elderly (PACE), a state program that assists low-income Pennsylvania seniors with drug costs, filled 52 percent more prescriptions than those with no coverage.

Atherly (2002) uses the 1995 MCBS and a model similar to that of Coulson, et al. (1995) and estimate the cost that supplemental insurance plans impose on Medicare. The first stage choice is between no supplemental coverage, employer-sponsored coverage, or Medigap coverage. The second stage is a regression of total Medicare Part A and B costs, with indicator variables for coverage type and terms to control for selection bias. Atherly (2002) finds some evidence of adverse selection on unobservables into plans with drug coverage, but the magnitude of the effect was not large. The moral hazard effect of Medigap plans on Medicare Part B (essentially outpatient services and medical equipment) was estimated as a 5 to 15 percent increase in the probability of any use and a 24 to 28 percent increase in the level of expenditures.

Lillard, Rogowski, and Kington (1999) use an instrumental variables (IV) approach to estimate the effect of supplemental insurance on seniors' drug spending. Their data source is the RAND Elderly Health Supplement to the 1990 Panel Study of Income Dynamics (PSID) and they examine the behavior of 910 individuals. Their set of instruments includes indicators for lagged drug

coverage, and measures of employment history. They find that insurance coverage for prescription drugs increases the probability of any drug use, and leads to a 19 percent increase in total expenditures (conditional on expenditures being positive), although the latter effect is not statistically significant effect.

III. Research Design

Fee-for-service (FFS) Medicare does not insure the vast majority of prescription drugs. The program covers only drugs administered in an institutional setting (e.g. hospital, nursing home), or belonging to very few special categories (e.g. immunosuppressives, hemophilia clotting factors) Medicare beneficiaries who want prescription drug coverage must seek it through supplemental insurance.

The four main supplemental insurance drug coverage sources for the elderly are 1.) Medicaid, which is a means-tested program that covers health care for the low income elderly and which is jointly administered by the states and the federal government, 2.) employer-sponsored private health insurance for retirees, 3.) self-purchased Medigap insurance policies, which offer standardized benefit packages (some of which cover drugs) designed supplement Medicare benefits, and 4.) Medicare + Choice (HMO) plans, which offer additional benefits beyond FFS Medicare such as prescription drugs.

In this study, we focus on the latter two types of supplemental insurance and do not analyze the behavior of individuals who reported coverage through Medicaid or a former employer. We exclude individuals with Medicaid, because Medicaid beneficiaries are likely to be unrepresentative of the Medicare population as a whole, and because Medicaid drug formularies and prescribing rules for physicians make it difficult to impute a price for prescription drugs. Further, we exclude those with private employer-sponsored insurance because we want to create a sample where our estimation strategy can identify the response of individuals to price changes. Our estimation strategy employs

instruments that apply only to individuals with Medigap and Medicare + Choice plans, and thus we do not include in our sample individuals with private insurance and those with Medicare. Another advantage of our sample section choice is that it results in a sample, which faces a drug coverage similar to the Medicare prescription drug benefits that have been recently proposed in the U.S. Congress.²

Medigap plans that cover prescription drugs typically offer a 50% coinsurance rate with an annual deductible of \$250, and an annual benefit cap of \$1,250 or \$3,000 depending on the specific type of plan.³ Medigap plans also cover beneficiary cost-sharing amounts for many services that are potentially complementary to prescription drug use (e.g. doctor visits). In most states, insurers are allowed to price Medigap policies on the basis of age and sex and may refuse coverage to individuals on the basis of their health status.⁴ While the federal government regulates some aspects of the Medigap market in the Omnibus Budget Reconciliation Act of 1990 (OBRA-90), many states have gone another step, enacting additional regulations about the sale and pricing of Medigap policies. This cross-state variation in the rules provide the instruments, which allow us to identify the demand curve for prescription drugs. As explained in more detail later, this cross-state variation in the rules for providing Medigap insurance satisfy the requirement for valid instruments, namely that the rules

² In contrast, the cost-sharing schemes in employer plans generally include sizable deductibles, making the incentive structure very different from that of Medicare + Choice, Medigap, or most of the Medicare prescription drug proposals, all of which typically feature "first dollar" coverage or very low deductible amounts.

³ Medigap plans were standardized (except in three states--more on this later) by the Omnibus Budget Reconciliation Act of 1990 (OBRA-90), which created 10 benefit packages, dubbed A-J. Plans H, I, and J are the only ones that cover prescription drugs; plan J has a \$3,000 per year benefit cap, while plans H and I cap benefits at only \$1,250. The GAO (2001) reports annual Medigap premiums per covered life to be about \$1,400 for plan H and about \$1,700 for plans I and J. For more details about Medigap plans, see Finkelstein (2000) or Lutzky, et. al. (2001).

⁴ However, if someone is already insured when his or her health changes for the worse, the policy is guaranteed renewable.

generate variation in Medigap availability and RX prices, while not directly affecting the drug consumption decisions.⁵

Medicare + Choice plans are managed care that are specifically targeted to Medicare beneficiaries. Health care services are provided by private HMOs who are then reimbursed a flat fee by the Medicare program. In order to attract Medicare beneficiaries from FFS, they typically offer more generous benefits (or less cost-sharing for existing benefits) than FFS Medicare. In 2001, for instance, 68 percent of Medicare + Choice plans offered some degree of drug coverage. The median drug plan offered co-payment amounts per prescription filled of \$5-15 for generics and \$20-40 for brand names. The median annual benefit cap for prescription drugs was in the \$1,000-1,500 range.⁶

Private HMOs must accept any Medicare beneficiary who desires to enroll, which would lead one to suspect that plans would suffer from adverse selection. In this case the moral hazard effect, i.e. the responsiveness to prescription drug prices is overstated when estimating the regression with OLS. However, evidence suggests that Medicare + Choice plans have largely overcome this problem by actively marketing their plans to younger, healthier seniors. In this case OLS understates the seniors' responsiveness to prices.

Our instruments for seniors with Medicare + Choice is the degree of penetration of HMOs at the county level and the county-specific flat reimbursement amount that Medicare pays HMOs for each beneficiary served. These variables are valid instruments if they are correlated with prescription drug prices, but do not affect seniors' drug consumption decisions. This is the case if an individual's (unobserved) demand for drugs is uncorrelated with overall market penetration or the relative generosity of the local Medicare+Choice providers (as proxied by the reimbursement amount).

IV. Empirical Model

⁵ Alternatively, if states with high drug demand respond enact policies that depress the price, then the regulation instruments are not exogenous to the system.

Our measure of prescription drug price is the average coinsurance rate, which we measure as the ratio of out-of-pocket expenses for individual i and the cost of the drug. Formally, we define the price P_i as

$$P_i = \frac{\text{Out-of-Pocket Drug Expenses}_i + \text{Uncollected Drug Liability}_i}{\text{Total Drug Expenses}_i} \quad (1)$$

which is the proportion of uncovered drug expenses.

This measure of price has two limitations.⁷ The first limitation is that we cannot generate a price variable for individuals who had zero drug spending. This affects less than ten percent of the sample, after excluding those with Medicaid and private insurance. Excluding this subsample will not adversely affect the consistency of our estimates (see, for example, Vella, 1998).

The second limitation is that our price measure introduces a second source of endogeneity (beyond self-selection into drug coverage) if an individual's insurance includes a deductible and/or a benefit cap. For example, if an individual faces a deductible, his or her average coinsurance rate will be a decreasing function of the total amount of drug spending. Thus, price and quantity consumed are determined simultaneously. However, this is not a serious limitation given that we will employ an instrumental variable estimation technique, which controls for both sources of endogeneity in the price variable.

We estimate two reduced-form models for the demand of prescription drugs. In the first model, the dependent variable is the total annual expenditure on prescription drugs from all payment sources. In the second model, the dependent variable is the total number of prescriptions filled in a year. Formally, our basic model is

$$\ln(Y_i) = \mathbf{a} + X_i\mathbf{b} + C_i\mathbf{g} + M_i\mathbf{m} + R_i\mathbf{r} + T_i\mathbf{t} + dP_i + e_i \quad (2)$$

⁶ Data compiled by authors from Medicare Compare database (<http://www.medicare.gov/>).

⁷ We also re-ran the analysis excluding uncollected liability from the price calculation, but results reported in the later part of this paper were not substantively different.

where Y represents, depending on the specification, either our drug expenditure or drug quantity measure, and where P is the coinsurance rate, or the price for prescription drugs.⁸ Control variables include a vector of demographic factors (X), medical conditions and other measures of health (C), other medical utilization (M), attitudes toward risk (R), and year indicators (T).

We use two dependent variables because insurance coverage can influence drug consumption in two ways—by increasing the amount of prescription drugs used and/or by inducing a move from less-expensive generic drugs to more-expensive brand name drugs. Of the 50 drugs most commonly used by seniors in the 1990s, 22 had generic or co-marketed versions available, suggesting that there is potential for substitution between more- and less-expensive versions of the same drug. (Families USA, 1999).

Our main concern is to control for potential endogeneity of our price variable. Our measure of price, i.e. the proportion of uncovered drug expenditures, is endogenous because individuals choose their coinsurance rate by choosing the type of insurance coverage. Put differently, unobserved variables, such as unobserved health conditions, affect both the coinsurance rate and the level of prescription drug use. Finally, and as mentioned previously, the price of insurance is endogenous because most insurers require the insured to cover a deductible, thus drug expenditures and the effective price are simultaneously determined. While we know the deductible amount for Medigap plans, we do not observe the deductible for our other source of supplemental drug coverage, Medicare + Choice.

Failure to account for the endogeneity leads to an inconsistent estimate of the coefficient on the price variable.⁹ Furthermore, it is difficult to determine the direction of this bias a priori. While

⁸ Since our quantity and expenditure variables are non-negative and are skewed to the right as typical for these types of health variables, we use the natural log of the response as the dependent variable. In our data, the mean number of prescriptions is about 20 relatively, and therefore we treat the number of prescriptions as a continuous variable in our regressions.

⁹ Of course, there is also the potential that the other medical utilization variables are endogenous. However, as we are not primarily interested in the effect of these variables, we make no attempt to control

the endogeneity of price introduced by the presence of a deductible will result in estimates of demand that are too elastic, it is more difficult to predict the direction of endogeneity bias due to self-selection into supplemental insurance. For example, suppose unhealthy individuals chose to obtain drug coverage plans. In this case the OLS coefficient on the price is overestimated in absolute value. On the other hand, if stringent underwriting standards in the Medigap market or proactive marketing by HMOs lead to healthier-than-average people obtaining coverage then OLS price coefficient will be underestimated.

To control for the potential endogeneity of the prescription drug price, we propose an instrumental variables (IV) estimator (Angrist & Krueger, 2001). Our instruments are 1.) the Medicare managed care penetration rate in the individual's county (Z_MCPEN), 2.) the Medicare managed care county-specific reimbursement rate (Z_REIMB), 3.) a dummy variable indicating whether state law requires an annual open enrollment or guaranteed issue period for Medigap insurance (Z_OPEN), and interaction of this variable with age ($Z_OPEN \times AGE$) and an interaction with an indicator for any serious medical condition ($Z_ANYCOND$), 4.) an indicator variable indicating whether state law requires community pricing (i.e. everyone pays the same premium, regardless of age) on Medigap plans (Z_COMM), and its interaction with age ($Z_COMM \times AGE$), 5.) an indicator variable indicating whether state law bans attained-age pricing, Z_BANAA (i.e. a pricing scheme such that premiums increase with age, regardless of what age the policyholder was when he or she purchased the policy), and its interaction with age ($Z_NANAA \times AGE$), and 6.) an indicator variable for states that do not use the standardized Medigap plans and instead allow individuals to purchase insurance riders to cover specific health care needs (Z_RIDER).¹⁰

Valid instruments are correlated with the prescription drug price, but uncorrelated with the error term in the second stage (equation 2). The county-level HMO penetration rate (the number of

for their endogeneity. This omission should in no way bias the coefficient estimates on the explanatory variable of interest.

elderly people enrolled in HMOs divided by the total number of elderly Medicare beneficiaries) is a valid instrument assuming that other people's insurance choices do not affect an individual's use of health care. Further, the penetration rate is not directly affecting an individual's drug consumption decisions since the Medicare + Choice penetration rate is largely a function of history. Enrollment in Medicare HMOs has been greatest where HMOs have historically played a large role in insuring working-age people, in California, for example.

Local variation in laws and policies can be a good source for instruments as long as individuals do not determine those laws and policies. We include the amount that the federal government reimburses HMOs for treating Medicare beneficiaries as an instrument because of its role as a proxy for Medicare + Choice plan generosity. The reimbursement amount depends on a complex formula that blends local and national historical spending levels for fee-for-service Medicare beneficiaries, but does not reflect the actual costs incurred by HMOs.¹¹ It has been well-documented that the reimbursement amount varies substantially across localities, and, as HMOs are required to actually spend the reimbursements on beneficiaries (less administrative and profit fees), that the reimbursement rate is highly correlated with the generosity of Medicare+Choice benefits. (Dallek, et. al., 2002) In fact, inter-county variation in reimbursement amounts exceeds the corresponding variation in health care costs, and the reimbursement amount is only weakly correlated with private health insurance premiums at the county level. (Dubow, 2001)

The reimbursement amount is a valid instrument if it affects demand only through the price mechanism. There are good reasons to think this is the case. First, prescription drug prices tend to be set nationally by the manufacturer and do not vary locally in the same way that hospital prices do. Second, Since FFS Medicare does not cover prescription drugs, local variation in drug utilization and/or pricing play no part in determining the reimbursement amount. However, if the coinsurance

¹⁰ These states are Massachusetts, Minnesota, and Wisconsin.

¹¹ For details of the reimbursement formula, see http://research.aarp.org/health/dd47_choice.html.

rates for various medical services are positively correlated with one another and with the reimbursement rate, i.e. Medicare+Choice HMOs offer generous coverage for other medical services that are complements to prescription drugs (e.g. doctor visits), then this instrument may not be exogenous.¹² However, we attempt to control for this potential effect by including doctor visits and hospital stays as explanatory variables.¹³

Our instruments for individuals with Medigap coverage come from state-level regulations. They include the previously mentioned open enrollment and pricing regulations, which make it easier for older people or those in poor health to obtain insurance.

We attempt to control for health status by using age, gender, self-reported health, and a vector of dummy variables for the presence of specific medical conditions. However, to the extent that we are unable to fully control for health status in the demand equation, there is potential for correlation between these Medigap instruments and the second stage residuals. We will also apply a formal test of over-identifying restrictions for zero correlation of the instruments with the residuals.

V. Data

We employ the Medicare Current Beneficiary Survey (MCBS), a cross-sectional survey of Medicare beneficiaries conducted by the Centers for Medicare and Medicaid Systems (CMS, formerly HCFA). This data set combines survey information with Medicare billing records and thus has very accurate data on health care utilization and expenditures.

We pool three years of MCBS data, 1996, 1997, and 1998.¹⁴ In order to arrive at a sample that allows us to identify the demand equation, we exclude any Medicare beneficiary under the age of

¹² Medicare + Choice HMOs are required by law to spend all the money that they receive as reimbursement from CMS (personal communication with Lisa Alexih, 12/10/01).

¹³ Additional background on Medicare + Choice payment rates is available at [http://www.nhpf.org/pdfs/8-758+\(web\).pdf](http://www.nhpf.org/pdfs/8-758+(web).pdf).

¹⁴ Nominal dollar amounts were adjusted to 1998 values using CPI (for income) or prescription drug price inflation (for drug expenditures). (Families USA, 2001).

65 because younger disabled beneficiaries are not necessarily eligible for Medicare + Choice or Medigap plans and tend to be covered by other forms of public insurance. We also excluded any individual who spent six or more months of the sample year in a nursing facility, as drug expenses are included in blanket facility charges and are not separately identifiable. We control for people who spent part of the year in a nursing facility or other institution by including the number of days residing in the community as an explanatory variable in the demand equation. Finally, and as noted previously, we also exclude individuals with Medicaid or employer-sponsored retiree coverage from the sample due to the difficulty in finding good instruments for these types of insurance.

A portion of the MCBS respondents have more than one year of data, creating an unbalanced panel. However, this feature of the data is difficult to exploit because more than half of all sample respondents are only interviewed for a single year. For this reason, we decided against attempting to apply a panel approach to modeling. To assure independence of observations, we include only a single year's observation for each individual; where individuals had multiple observations, we chose the most recent year in which they had positive drug expenditures.

After applying these selection criteria, in the sample remain individuals with fee-for-service Medicare only (those individuals may also participate in state and local public insurance plans), Medicare + Choice managed care coverage; and individually-purchased Medigap coverage.

Data for some of our instruments come from county-level CMS data on Medicare HMO penetration and reimbursement rates. The penetration rate is calculated as the number of Medicare beneficiaries enrolled in managed care divided by the total number of Medicare beneficiaries in the county. We predict that larger penetration leads to lower drug prices, as higher penetration results in a higher likelihood of gaining drug coverage through an HMO. The reimbursement rate is the monthly payment provided by CMS to the private HMO for each Medicare beneficiary served. The reimbursement rate is determined by a complicated formula that incorporates local and national

trends in health care spending and we predict that this variable is positively correlated with the generosity of drug coverage offered by HMOS, hence negative correlated with drug prices.¹⁵

The data for our Medigap instruments come from Lutzky, et. al.'s (2001) study of state-level regulations of the Medigap insurance market. We included four variables (and related interaction terms)--whether the state require insurers to offer an open enrollment period (during which policies are guaranteed issue); whether the state require insurers to community-rate their policies (offer the same price to everyone, regardless of age or health status); whether the state bans attained-age pricing (a pricing scheme in which premiums increase with the policyholder's age); and whether the state allows insurers to sell coverage for specific medical services (e.g. drugs) as riders to a basic Medigap policy.

Table 1 provides summary statistics presents summary statistics for the various dependent and explanatory variables used in estimating seniors' demand for prescription drugs. The table shows that the average coinsurance rate (henceforth price) faced by an individual over the course of the survey year is 0.75. Mean drug expenditures are \$739 (in constant 1998 dollars) and the mean number of prescriptions filled is 22.24. The distributions of both drug expenditures and the number of prescriptions filled, like most health care data, are highly skewed to the right.

Table 2 shows the unconditional difference in utilization and expenditures among different insurance groups. Medigap drug expenditures are the largest, both in dollars and number of prescriptions. People with HMO drug coverage fill about ten percent fewer prescriptions and spend approximately twenty percent less than those with Medigap drug coverage. Also, Table 2 shows that there is variation in average coinsurance rates across insurance categories. Seniors with no supplemental insurance paid 89 percent of their total prescription drug bill out-of-pocket (this proportion is not exactly one because there are some state and local programs assist some seniors

¹⁵ The data are for December of the relevant calendar year and are available online at <http://www.hcfa.gov/medicare/mgd-rept.htm>.

with drug expenses), while seniors with Medigap pay 70 percent, and those in HMOs pay 47 percent of their drug expenses out-of-pocket. Although not shown in Table 2, there is also considerable variation in the calculated coinsurance rates within coverage categories. Table 3 summarizes the state-level Medigap regulations.

VI. Results

The OLS results in Table 4 provide a benchmark against which we compare our IV estimates. In the first two columns we report the results of the log-linear model, which explain either the $\log(\text{expenditure})$ (Table 4, column 1) or $\log(\text{quantity})$ (Table 4, column 2) with the drug price.

The OLS price coefficients in all specifications are statistically significant. Given that we estimate a log-linear model, the coefficient on price is not an elasticity but measures the percentage change in Y for a unit change in P (which is measured as a proportion). We will refer to this price coefficient as a *semi-elasticity* in our discussion. The effects of the other covariates are presented in Appendix A1. Most signs are as expected and many explanatory variables are statistically significant. Interestingly, the regression results show that log income is strongly associated with drug expenditures, but is much less so with the quantity measure. For example, the income elasticity of drug expenditures is estimated to be 0.140 (Appendix A1, column 1), and 0.026 for the number of prescriptions filled (Appendix A1, column 2).¹⁶

The price coefficient estimate in Table 4, column 3 implies that a ten percentage point increase in the coinsurance rate is associated with a 10.7 percent decrease in the level of expenditures.¹⁷ The quantity of drugs consumed is less responsive to prices. Here a ten percent increase in the price leads to a six percent decrease in the quantity of drugs consumed. As noted

¹⁶ The price elasticity of expenditures is statistically significant at the 0.001 level, but the price elasticity of quantity is not statistically significant at the five percent level.

¹⁷ The coefficient estimate gives the effect of an infinitesimal change. For a larger change in price, we evaluate the proportional change in demand as $\Delta Y/Y = \exp[\delta(\Delta P)] - 1$.

previously, we expected to find that expenditures are more responsive to the price than drug quantities, because expenditures can be relatively easily altered when consumers chose to purchase generic drugs instead of brand name drugs.

Since the OLS price coefficients are likely biased, we estimate the price coefficients using two-stage least squares. We report some of the first stage results in Table 5. The table presents results from a first-stage OLS regression of the potentially endogenous repressor (P) on the vector of instruments (Z). Although not reported in this table, the regressions include all other exogenous second-stage regressors (X, C, M, R, T).

Table 5 shows that our instruments are significantly correlated with the drug price variable, as required by our instrumental variable method. The HMO instruments are statistically significant at the individual and joint levels. While the Medigap instruments are statistically insignificant at the individual level (with the exception of Z_OPEN, its interaction with age, and Z_RIDER), they are significant when assessed as a group (Table 5B). Based on the results of these tests, the instruments satisfy the criteria that they are correlated with our right hand side endogenous variable.

Table 6 shows the instrumental variable estimate counterparts to the OLS estimates presented in Table 4. The row at the bottom of the table presents the results for the overidentifying restrictions test. Drug prices continue to be an economically and statistically significant predictor of demand behavior, supporting the moral hazard hypothesis. Compared to the OLS estimates in Table 4, the standard errors on the estimates increase; however, the point estimates remain statistically significant at conventional levels.

While the coefficient on expenditures decreased from -1.07 in Table 4 to -0.91 in Table 5, the coefficient on quantity has increased from -0.56 in the OLS model to -0.97. The discrepancy between the elasticity estimates for expenditures and quantity in Table 4 disappeared and now the quantity and expenditure estimates are fairly similar to each other. The test of overidentifying

restrictions rejects the null hypothesis of no correlation between the instruments and error term in the expenditure equation.¹⁸

We interpret the difference in coefficient estimates in the quantity equation as evidence of selection effects. Because the (consistent) 2SLS estimate is larger in absolute value than the (inconsistent) OLS estimate, we conclude that this is evidence of favorable selection into supplemental drug coverage, meaning that healthier individuals tend to obtain insurance that covers drugs. Because individuals who tend to use fewer drugs tend to have better coverage, the high elasticity of demand is masked in the OLS models. Underwriting or HMO marketing practices appear to result in an insured population that is less prone to use drugs than the general population, even after controlling for a variety of observable health measures.

The instrumental variable results show that prescription drug price decreases result in a roughly equal increase in both drug consumption and expenditures (-0.97 vs. -0.91). This suggests that there is only little substitution of brand for generics drugs in response to price changes. This may be in part because HMO drug plans tend to strongly encourage the use of generics over brand drugs with tiered copays (e.g. \$10/generic and \$25/brand script is pretty common) and formularies that require the member to fill generic where available. Another possible explanation for this finding is that all Medigap and many HMO plans have benefit caps (a maximum dollar amount of benefits paid for prescription drugs) and that seniors prefer not to exhaust their benefits by substituting more expensive brand for cheaper generic drugs.

The coefficients on the other control variables are similar to those in the OLS estimates reported in the Appendix. We do not report those results here, but it is noteworthy that the relationship between income and drug demand is essentially unchanged from the OLS case.

¹⁸ Angrist (1991) argues that the test for overidentifying restrictions is a test that examines whether the instrumental variable estimates are the same across two sets of instruments. Thus, rejecting the null

VII. Conclusions

We estimated a demand curve for prescription drugs using a sample of elderly Medicare beneficiaries. Our explanatory variable of interest was the average coinsurance rate, which is the proportion of total drug costs for which the individual is liable. Because the coinsurance rate is potentially endogenous, we estimated the demand equation via two-stage least squares (2SLS). We used as instruments state regulatory practices, managed care market penetration, and Medicare reimbursement policy.

We found that a one percentage point increase in the coinsurance rate to be associated with a 0.91 percent decrease in the total expenditure level and a 0.97 decrease in the number of prescriptions filled, conditional on use being positive.¹⁹

These estimates of prescription drug demand are considerably greater than those observed in studies of the working-age population (e.g. the estimates of -0.5 reported in the RAND HIE or the estimates of -0.1 to -0.3 reported in the review by Smith and Kirking, 1992). These results suggest that any attempts to estimate the cost of a Medicare prescription drug benefit have to take the behavioral response into account that is associated with lower prices. Our estimates are larger than even the findings of Coulson, et.al., who found that an 82 percent subsidy was associated with an increase in quantity demanded of only 28 percent. The Coulson, et. al estimates imply a price coefficient of only 0.34, significantly lower than the coefficient of 0.97 estimated here.

Seniors' demand for prescription drugs appears to be, at least on average, more price-sensitive than that of younger groups (Newhouse 1993). One potential explanation is that seniors tend to take more drugs for chronic conditions, while younger groups' drug use is more associated with acute conditions. If out-of-pocket drug costs are high, it may cause less disutility to limit

hypothesis does not necessarily imply that the instruments are invalid.

¹⁹ The larger effect of price on quantity than on expenditures may reflect behavior on the part of HMOs to encourage their members to choose generics where possible, through the use of tiered copayments or formularies.

consumption of drugs for chronic conditions (e.g. arthritis or hypertension) than it is to limit consumption of drugs for acute conditions (e.g. pneumonia). Investigating the reason for this difference in price sensitivity could be a fruitful direction for future research.

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Table 1
Descriptive Statistics for Explanatory Variables

Variable Name & Description	Mean	Std. Dev.	Min.	Max.
<i>Prescription Drug Demand</i>				
RXEXPEND (Expenditures on Rx drugs during calendar year, \$1998)	739.908	891.645	0.521	30175.38
RXSCRIPT (Number of prescriptions filled during calendar year)	22.243	20.593	1	233
<i>Prescription Drug Price</i>				
PRICE (Mean coinsurance rate for Rx drugs – see equation 1)	0.752	0.318	0	1
<i>Prescription Drug Coverage (D)</i>				
I_GAPRX (DV: =1 if have Medigap plan with drug coverage)	0.193	0.395	0	1
I_HMORX (DV: =1 if have Medicare+Choice plan with drug coverage)	0.253	0.435	0	1
<i>Demographic (X)</i>				
X_AGE (age in years)	76.873	7.590	65	105
X_FEMALE (DV: =1 if female)	0.591	0.492	0	1
X_INCOME_K (Personal income, 000's of \$1998)	16.051	19.248	0	888.5625
X_BLACK (DV: =1 if African-American race)	0.074	0.262	0	1
X_METRO (DV: =1 if live in MSA)	0.698	0.459	0	1
X_CDAY (# days spent in non-facility setting)	360.071	25.090	181	366
X_MARRY (DV: =1 if married)	0.515	0.500	0	1
X_ED_COL (DV: =1 if college graduate)	0.119	0.324	0	1
X_ED_HSG (DV: =1 if high school grad or some college)	0.319	0.466	0	1
X_G_NE (DV: =1 if live in Northeastern U.S.)	0.186	0.389	0	1
X_G_SOUTH (DV: =1 if live in Southern U.S.)	0.357	0.479	0	1
X_G_WEST (DV: =1 if live in Western U.S.)	0.215	0.411	0	1
<i>Health Conditions (C)</i>				
C_ARTH (DV: =1 if history of arthritis)	0.602	0.490	0	1
C_BONE (DV: =1 if history of osteoporosis, broken hip)	0.173	0.378	0	1
C_CANCER (DV: =1 if history of cancer of any type other than skin cancer)	0.196	0.397	0	1
C_CARDIO (DV: =1 if history of atherosclerosis, hyper-tension, AMI, angina pectoris, or other heart condition)	0.727	0.446	0	1
C_DIAB (DV: =1 if history of diabetes)	0.155	0.362	0	1
C_LUNG (DV: =1 if history of emphysema)	0.143	0.350	0	1
C_ORGB (DV: =1 if history of Alzheimer's, Parkinson's)	0.045	0.208	0	1
C_PSY (DV: =1 if history of mental illness)	0.030	0.170	0	1
C_STROKE (DV: =1 if history of stroke)	0.119	0.324	0	1
C_ANYCON (DV: =1 if any of above conditions except arthritis)	0.838	0.369	0	1
C_H_POOR (DV: =1 if reported health as 'poor')	0.068	0.251	0	1
C_H_FAIR (DV: =1 if reported health as 'fair')	0.170	0.376	0	1

C_H_GOOD (DV: =1 if reported health as 'good')	0.331	0.471	0	1
C_H_VERY (DV: =1 if reported health as 'very good')	0.283	0.450	0	1
C_ADL (DV: =1 if 1+ ADL impairments)*	0.053	0.224	0	1
C_IADL (DV: =1 if 1+ IADL impairments, no ADLs)*	0.223	0.416	0	1
<i>Medical Utilization (M)</i>				
M_DOCVIS (# of office visits in CY)	4.500	5.821	0	87
M_IPSTAY (DV: =1 if had any inpatient hospital stay in CY)	0.175	0.380	0	1
<i>Risk Proxies (R)</i>				
R_SMOKE (DV: =1 if smoke currently)	0.107	0.309	0	1
R_QUIT (DV: =1 if smoked, but quit)	0.481	0.500	0	1
R_FLUSHO (DV: =1 if had optional flu shot in past year)	0.704	0.456	0	1
<i>Instruments (Z)</i>				
Z_MCPEN (county-level percentage of Medicare beneficiaries enrolled in managed care, Dec. of CY)	15.287	15.251	0	54.63
Z_REIMB (Medicare's monthly reimbursement amount (\$) to HMOs in county of residence)	466.705	99.862	229.7	782.7
Z_OPEN (DV: =1 if state requires Medigap open enrollment period)	0.152	0.359	0	1
Z_COMM (DV: =1 if state requires community pricing of Medigap plans)	0.144	0.351	0	1
Z_BANAA (DV: =1 if state bans attained-age pricing of Medigap plans)	0.118	0.323	0	1
Z_RIDER (DV: =1 if state allows sale of Medigap riders)	0.060	0.238	0	1
<i>Time Dummies (T)</i>				
T_98 (DV: =1 if data record from 1998)	0.389	0.488	0	1
T_97 (DV: =1 if data record from 1997)	0.287	0.452	0	1

*Note: ADL stands for Activity of Daily Living (bathing, transferring to/from a chair, dressing, eating, and using the toilet) and IADL stands for Instrumental Activity of Daily Living (paying bills, using the telephone, shopping, housework, and preparing meals). Needing assistance from another person to perform these tasks is used to measure functional impairment, with ADLs representing more serious impairment than IADLs.

Table 2
 Prescription Drug Use
 (in drug inflation-adjusted \$1998)

Coverage Status	N	Mean Coinsurance*	Mean Expenditure	Mean number of Prescriptions
No Coverage	4,422	0.890	\$725.55	22.2
HMO Drug	1,980	0.470	\$676.63	21.5
Medigap Drug	1,511	0.703	\$863.80	23.3
All Groups**	7,829	0.752	\$739.91	22.2

Note: Dollar amounts are real 1998 drug inflation-adjusted. The prescription drug-specific inflation rate was 4.1% per year. **Each year? Are results sensitive to this inflation adjustment?**

Source: Medicare Current Beneficiary Survey (1996-1998); Families USA (2001), *Enough To Make You Sick: Prescription Drug Prices for the Elderly*.

* Individual Coinsurance rates were calculated as (out-of-pocket expenses + uncollected liability) / total expenses.

** Column totals do not sum because 118 people reported having both HMO and Medigap drug coverage.

Table 3
Medigap Regulation in the States, 1997.

State	Year Enacted	Open Enrollment?	Mandatory Community Rating?	Riders?
Arkansas	1993	No	Yes	No
California	1997	Annual	No	No
Connecticut	1993	Always	Yes	No
Maine	1993	Annual	Yes	No
Massachusetts	1994	Annual	Yes	Yes
Minnesota	1993	No	Yes	Yes
New York	1993	Always	Yes	No
Washington	1995	No	Yes	No
Wisconsin	1990	No	No	Yes

Note: Mandatory community rating requires insurers to charge the same premium to all eligible purchasers. Open enrollment requires insurers to sell policies to individuals regardless of their health condition. "Always" implies this regulation is in effect year-round, whereas "Annual" means that open enrollment is limited to a certain time period during the year. States with riders allow the purchase of Medigap insurance on a benefit-by-benefit basis (i.e. you don't need to buy a standardized "package" of benefits).

Source: Lutzky, et.al. (2001), p.4.

Table 4:
 OLS Results of the RX Drug Demand Model
 Estimated Coefficients and Standard Errors in Parentheses

Dependent Variable	ln(expenditure)	ln(quantity)
Prescription Drug	-1.070	-0.559
Price	(0.043)	(0.036)
Other Control Vars?	YES	YES
Model R ²	0.304	0.309

Note: N=7,829. The control variables in columns 1 and 2 are the demographic variables, health condition variables, risk proxies, medical utilization variables, and year indicators as listed in Table 1.

Table 5A
 First Stage Estimates and the Validity of Instruments
 Dependent Variable: Prescription Drug Price
 Coefficient Estimates and Standard Errors in Parentheses

Variable	Coefficient Estimate	t-Statistic
<i>HMO Instruments</i>		
Z_MCPEN	-0.0038 (0.0004)	-9.28
Z_REIMB	-0.0002 (0.0000)	-4.60
<i>Medigap Instruments</i>		
Z_OPEN	0.2391 (0.1066)	2.24
Z_OPEN x AGE	-0.0028 (0.0014)	-2.03
Z_OPEN x ANYCOND	-0.0266 (0.0238)	-1.12
Z_COMM	-0.0477 (0.1084)	-0.44
Z_COMM x AGE	0.0013 (0.0014)	0.92
Z_BANAA	-0.0844 (0.1035)	-0.82
Z_BANAA x AGE	0.0008 (0.0013)	0.59
Z_RIDER	0.0373 (0.0149)	2.51

Table 5B
 Joint Significance Tests for Candidate Instruments

Instruments	F-Statistic (DOF)	Prob > F
HMO	101.74 (2, 7783)	0.0000
Medigap	5.27 (9, 7783)	0.0000

Table 6
 2SLS Results of the RX Drug Demand Model
 Estimated Coefficients and Standard Errors in Parentheses

Dep. Var.	ln(expenditure)	ln(quantity)
Prescription Drug	-0.907	-0.971
Price	(0.218)	(0.180)
Other Control	YES	YES
Vars?		
R ²	0.302	0.298
Test of Overident.		
Restrictions		
NR ² ~ X ² [9]	21.036	8.865
p-value	0.012	0.405

Note: N=7,829. The control variables in columns 1 and 2 are the demographic variables, health condition variables, risk proxies, medical utilization variables, and year indicators as listed in Table 1.

Appendix A1
 OLS Results of the RX Drug Demand Model
 Estimated Coefficients and Stand Errors in Parentheses

Variable	log(expenditure)	log(quantity)
PRESCRIPTION DRUG	-1.070	-0.559
PRICE	(0.032)	(0.036)
X_AGE	-0.111	-0.109
	(0.032)	(0.027)
X_AGE_SQUARED	0.001	0.001
	(0.002)	(0.000)
X_LOG_INCOME	0.140	0.026
	(0.021)	(0.018)
X_FEMALE	0.229	0.210
	(0.031)	(0.025)
X_BLACK	-0.115	-0.040
	(0.050)	(0.042)
X_METRO	-0.119	-0.059
	(0.029)	(0.024)
X_CDAY	0.003	0.003
	(0.001)	(0.000)
X_MARRY	0.065	-0.004
	(0.029)	(0.024)
X_ED_COL	0.032	-0.060
	(0.042)	(0.035)
X_ED_HSG	-0.022	-0.028
	(0.103)	(0.024)
X_G_NE	-0.102	-0.092
	(0.040)	(0.033)
X_G_SOUTH	0.052	0.051
	(0.033)	(0.028)
X_G_WEST	-0.240	-0.159
	(0.039)	(0.032)
C_ARTH	0.114	0.100
	(0.027)	(0.022)
C_BONE	0.144	0.088
	(0.035)	(0.029)
C_CANCER	-0.001	-0.029
	(0.032)	(0.027)
C_CARDIO	0.712	0.673
	(0.029)	(0.024)
C_DIAB	0.332	0.327
	(0.036)	(0.030)
C_LUNG	0.253	0.279
	(0.037)	(0.031)
C_ORGB	0.086	0.012
	(0.065)	(0.054)

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C_PSY	0.278 (0.076)	0.217 (0.063)
C_STROKE	0.185 (0.040)	0.144 (0.033)
C_H_POOR	0.546 (0.064)	0.542 (0.054)
C_H_FAIR	0.501 (0.048)	0.489 (0.040)
C_H_GOOD	0.328 (0.040)	0.272 (0.034)
C_H_VERY	0.153 (0.040)	0.084 (0.034)
C_ADL	0.172 (0.065)	0.204 (0.054)
C_IADL	0.056 (0.033)	0.108 (0.027)
Year Dummy 1998	0.156 (0.032)	0.124 (0.025)
Year Dummy 1997	0.037 (0.032)	0.044 (0.027)
M_DOCVIS	0.049 (0.002)	0.030 (0.002)
M_IPSTAY	0.150 (0.036)	0.142 (0.030)
R_SMOKER	-0.052 (0.046)	-0.051 (0.038)
R_QUIT	0.063 (0.029)	0.063 (0.024)
R_FLUSHOT	0.214 (0.028)	0.193 (0.024)
CONSTANT	8.330 (1.242)	4.966 (1.033)
R-SQUARED	0.30	0.31