Persistence in Medicare Prescription Drug Expenditures by Treatment Class

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ABSTRACT

The chronic nature of many prescription drugs used by Medicare beneficiaries suggests that adverse selection could pose a problem in the market for stand-alone prescription drug plans that were created under the Medicare Modernization Act of 2003. Using panel data on the Medicare population from the Medical Expenditure Panel Survey, we find that prescription drug expenditures are less concentrated but more persistent over time than are total health expenditures. We also find that information on drug treatment categories increases the power of prediction models. Such information could be useful in developing improved risk adjustment models designed to minimize adverse selection.

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Introduction

The passage of the Medicare Modernization Act (MMA) in 2003 has focused attention on stand alone prescription drug insurance policies for Medicare beneficiaries. Prior to the MMA, stand alone prescription drug plans were not commonly available in the current health care system either to Medicare beneficiaries or others covered by private group and non-group insurance. This means there is little private market experience to guide the implementation of this new Medicare policy. It also raises the question of why stand alone drug policies were not commonly available. One possible reason for the lack of such policies is the problem of adverse selection which can threaten the efficiency and stability of an unsubsidized private insurance market. The MMA legislation implicitly recognizes this possibility by requiring the development of risk adjustment methods to reimburse insurers and by mandating substantial subsidies to premiums in order to attract both low and high risk beneficiaries to the plans. Additional legislative provisions to minimize adverse selection include reinsurance and risk corridors that shield insurers from bearing the full financial risk of prescription drug plans in the early years of the program. Finally, there are provisions that penalize beneficiaries who do not enroll in a prescription drug plan (PDP) immediately upon gaining Medicare eligibility.

Despite the various provisions written into the MMA, the chronic nature of many prescription drugs used by Medicare beneficiaries suggests that adverse selection could still pose a problem for the stability of the market over time. Adverse selection occurs when high risk persons, those with higher probabilities of having high expenditures, are

more likely to purchase the insurance policies than are low risk persons. This can happen when individuals are better able to predict their future health expenditures than are insurers who therefore can't adjust the premiums to reflect higher levels of risk. Adverse selection also occurs, however, when policies are required to be sold at community rated premiums which are not adjusted for individual variation in risk. The MMA requires that stand along drug plans be sold at community rated premiums. In this type of market, even a small degree of adverse selection on the part of beneficiaries may lead to premium increases that eventually drive low risk beneficiaries out of the market.

It is well known that many of the medical conditions for which Medicare beneficiaries use prescriptions drugs are chronic in nature, such as arthritis, high blood pressure, high cholesterol, diabetes, mental illness, ulcers, allergies and others (Boccuti, Moon, Dowling, 2003). Since prescription drugs for such chronic conditions are usually prescribed to be taken on a maintenance basis, this suggests that high levels of expenditures for prescription drugs may persist year after year among Medicare beneficiaries with certain chronic conditions. In fact, evidence shows prescription drug expenditures are easier to predict than expenditures for other types of health care services such as physician office visits and hospital stays (Pauly and Zeng, 2003; Wrobel et al 2004). Even among chronically ill beneficiaries, the probability of continued prescription drug purchases may be easier to predict than the probability of visiting the physician or requiring a hospital stay. One implication of this finding is that Medicare beneficiaries who anticipate persistently high drug expenditures may be more likely to enroll in a PDP than low risk beneficiaries when premiums are community rated. A second implication of the predictable nature of prescription drug expenditures is that insurers have an

incentive to avoid high risk beneficiaries, unless risk adjusted payments are able to compensate for their higher costs. Thus, two potential threats to the efficiency and stability of the market for PDPs exist when adverse selection is present.

In this paper we make use of nationally representative data on the non-institutionalized Medicare population to predict individuals' future prescription drug expenditures. We use information on year one's prescription drug use in order to predict year two's prescription drug expenditures. The information on year one's use of drugs is data that would be readily available to insurers from their claims databases. In our data each prescription drug purchase is associated with a therapeutic class and subclass. Therapeutic class and subclass indicate the main treatment purpose of the drug and thus reveal information on the health conditions of the drug user. For example, the purchase of an anti-cholesterol drug indicates that the person likely has high cholesterol. The therapeutic class and subclass information is similar to having medical condition data of the type that is coded on physician and hospital claims. In some instances, a drug purchase provides more important information than a medical diagnosis. For example, when diabetes is identified through a drug purchase the disease may be more serious than diabetes identified through a medical diagnosis since the physician coded diagnosis includes those who do and do not need insulin. As another example, hypertension can be treated several different types of drugs (diuretics, beta blockers, ACE inhibitors, etc.) which vary considerably in terms of their cost. Information on the drugs used to treat the condition, therefore, may provide more information than a medical diagnosis of hypertension.

Our study evaluates the statistical power of drug therapeutic information to

predict next year's expenditures using the current year's experience. Our models also control for a wide array of health status and socio-demographic characteristics. Two year panels from the 1996 through 2000 Medical Expenditure Panel Survey are pooled together. Unlike private prescription drug claims data sets, these data are representative of the entire non-institutionalized Medicare population. We pay particular attention to treatment categories that are associated with Medicare-Medicaid dual eligibles and other low-income and disabled Medicare beneficiaries. These groups are eligible for substantial subsidies under the MMA but may have risk factors that make them less attractive to insurers offering stand-alone prescription drug plans.

Previous Literature

There is a large literature focused on predicting total health care costs (see Moeller, JF, et al. 2003) and developing risk adjustment methods for the Medicare population (see Pope, GC, Ellis, RP, Ash, A, et al, 2000). Most of this research focuses on the use of inpatient and ambulatory claims based diagnostic condition coding to predict future health care costs. Some papers have examined the use of pharmacy based therapeutic condition codes but very few of these papers focus on the prediction of prescription drug costs (see Zhao, Y., Ellis RP, Ash AS, et al. 2001). In a recent paper, Wrobel, et al (2004) predict prescription drug costs for the Medicare population comparing several models including one based on the CMS' diagnosis cost group/ hierarchical condition category (DCG/HCC) risk adjustment model. However, they do not have access to pharmacy based therapeutic condition codes.

Pauly and Zheng (2003) examine the problem of adverse selection in the market

for PDPs. Using claims data for the under 65 population, they find that prescription drug expenditures are more predictable than other types of health care expenditures. In any given year, prescription drug expenditures show a similar degree of concentration as other types of health care expenditures, but over time persons who were in the top quintile of prescription drug expenditures are more likely to remain in the top quintile compared to persons who were in the top quintile of expenditures in other categories. According to Pauly and Zheng, adverse selection is more likely when there is a greater degree of persistence of high expenditures over time for two related reasons. First, persistence is high so it is easy to predict next year's expenditures. Second, risk averse people who are willing to pay above expected costs in order to reduce their risk of an unanticipated high cost event are not willing to pay as much of a risk premium to avoid the high but predictable expenditures associated with chronic prescription drug expenditures. Pauly and Zheng extrapolate their findings to the Medicare population and estimate that the premium for a stand alone drug policy would have to be subsidized in the range of 71 to 91 percent of the total cost in order for 80 percent of Medicare beneficiaries to purchase it.

Methods

In this paper, we use population based survey data on Medicare beneficiaries that follows individuals for a period of two years. Specifically, to predict an individual's "year two" prescription drug expenditures we use information from the individual's "year one" prescription drug utilization. These models are estimated using ordinary least squares (OLS) regressions with probability weights and corrections for the MEPS

complex sample design and can be characterized by the following equation:

$$RxExp_2 = \alpha + \beta_1 TC_1 + \beta_2 TSC_1 + \beta_3 Demo_1 + \beta_4 RxExp_1 + \varepsilon$$

The dependent variable ($RxExp_2$) is total drug expenditures in year two expressed in 2000 U.S. dollars. The key independent variables are sets of dummy variables that indicate whether each individual filled one or more prescriptions in each of 13 therapeutic classes (TC_1) or 59 subclasses (TSC_1) in year one. The more detailed set of dummy variables categorizes drugs in over 200 therapeutic subclasses, but to avoid overfitting the models we omit subclasses that contain fewer than 15 sampled persons in any of the subpopulations that we examine. Since therapeutic subclasses are nested within therapeutic classes we never include both types of variables in a single model, but we compare the predictive power of these two sets of variables across model specifications. We also examine the explanatory power of our therapeutic class and subclass variables in combination with an extensive set of year one socioeconomic and health status variables ($Demo_1$) and with year one total drug expenditures ($RxExp_1$).

We are interested in testing the predictive power of information drawn from the therapeutic categories of prescription drugs. Prescription drug therapeutic classes and subclasses are of interest in risk adjustment models for two major reasons. One, the data could be easily drawn from pharmacy based claims records and could be readily available to insurers in a timely manner. Two, in some cases, the identification of a chronic condition by the use of certain drugs used to treat the condition provides more information than the identification of a chronic condition by medical records. Chronic

conditions are likely to be more severe when beneficiaries are treating them with prescription drugs compared to those conditions identified by medical records alone. Therefore, prescription drug utilization data may also be useful for refining existing risk adjustment methods. The main drawback of relying on therapeutic information based on prescription drug use is that off-label use of drugs may not be properly accounted for and some drugs have a variety of labeled uses. In our data set therapeutic information is based on the most common reasons for prescribing the drug. Some drugs, however, are more likely to be used for off-label purposes than others.

For comparative purposes, we contrast the predictive power of therapeutic categories based on prescription drug purchases with models that include medical condition information, collected from household respondents. We construct two medical condition variables that are at similar levels of aggregation as the drug therapeutic class and subclass variables. Aggregate medical conditions (AgCond) consists of 12 dummy variables while detailed medical conditions (DeCond) consists of 50 dummy variables that indicate whether an individual has reported one of the aggregate or detailed medical conditions. In some variations of our model, we substitute the medical conditions variables for the therapeutic class variables to compare their explanatory power in predicting prescription drug expenditures. The models are characterized as follows:

$$RxExp_2 = \alpha + \beta_1 AgCond_1 + \beta_2 DeCond_1 + \beta_3 Demo_1 + \beta_4 RxExp_1 + \varepsilon$$

Since detailed conditions are nested within aggregate conditions we never include both types of variables in a single model.

Finally, for comparison purposes, we predict total non-drug and total health expenditures using either drug therapeutic subclasses or detailed medical conditions. If drug therapeutic categories prove to be significant predictors of prescription drug expenditures, then they may also be convenient and significant predictors of other types of health expenditures.

To compare various models in terms of their predictive power, we use linear regression models where the dependent variable is measured in dollars. This functional form is widely used in the risk adjustment literature (Pope, GC, RP Ellis, AS Ash, et al., 2000) because of its ease of interpretation. Also, the R-square is a standard measure of the fit of the model and, in this case, provides a measure of the degree to which second year expenditures can be predicted by the independent variables. To more accurately compare the measures of R-Square across different specifications and subsamples we construct standard errors for each R-square using balanced repeated replicates (BRR). We use 128 random samples which are drawn accounting for the strata and primary sampling units (PSUs) used in the MEPS. Next, regressions are run and the resulting R-square is computed 128 times using these randomly drawn subsamples which are approximately half the size of the original sample. Finally, standard errors are computed using the variation of these 128 estimates of R-square around the estimate of R-square from the original model.

After demonstrating the predictive power of prescription drug therapeutic categories we develop scores to assess the relative risk of specific groups of Medicare beneficiaries. We predict prescription drug expenditures for every individual in our

sample, using a regression model that includes therapeutic subclass indicators, sociodemographic and health status measures. Then for every individual we compute the ratio of the predicted expenditures to the mean. We report relative risk scores, expressed as percentages of the mean, for policy relevant groups. Thus, the relative risk scores identify those groups who are predicted to have higher or lower relative costs. Groups with higher predicted costs may be vulnerable to risk selection on the part of insurers if government reimbursement methods do not adequately account for their high risks. Particular attention is warranted for the more vulnerable Medicare populations including the disabled and those who are currently eligible for both Medicaid and Medicare.

Data

The data for this study are based on two year panel files from the Medical Expenditure Panel Survey (MEPS). The MEPS is a household survey representative of the U.S. civilian, non-institutionalized population and collects data on health utilization and expenditures, sources of payment, insurance coverage, employment, income, and individual and family sociodemographic characteristics including various measures of health status and medical conditions. The MEPS is designed as overlapping two year panels. Households are interviewed five times over a two year period of study and a new panel is begun each year. For this study, we combine data from the first four panels of the MEPS: Panel 1 was followed for 1996 and 1997, Panel 2 was followed for 1997 and 1998, and so on through Panel 4 which was followed for 1999 and 2000. We pool all four panels together in order to increase our sample size and improve the ability to predict expenditures for smaller subgroups. We rename all variables so that they refer to

year 1 or year 2 of their respective panels. To predict total prescription drug expenditures in year 2 we use information from year 1.

The MEPS contains detailed information on each drug purchased by sampled individuals including the total price paid for the drug, the medication name and the National Drug Code (NDC). We assign a therapeutic class and subclass to each drug purchased by using the NDC to link the MEPS prescribed medicines files to the Multum Lexicon database, a product of Cerner Multum, Inc. The Multum therapeutic classification system categorizes drugs in a manner which is designed to replicate the type of organizational schemes used in practice by physicians and pharmacists.[1]

For purposes of this paper, we include persons of any age with 12 months of Medicare coverage in year two of their panel. Thus, we include persons who were just starting their Medicare period of eligibility. We exclude persons who died or were institutionalized during the second year of the panel. By pooling four panels together our sample is larger and we can examine smaller subpopulations of policy interest such as the disabled Medicare beneficiaries under age 65 as well as those with Medicaid coverage. By pooling several years of data, however, we are ignoring changes over time in the patterns of prescription drug utilization. For example, between 1997 and 2001 the number of Medicare beneficiaries who purchased cholesterol lowering drugs increased from 4.9 to 10.5 million. During the same time period, the number of Medicare beneficiaries who purchased COX-2 inhibitors, a new subclass of analgesics, increased from 0 to 5.5 million (Moeller, et. al. 2005). Changes in the patterns of drug prescribing will continue to occur as new drugs are developed and introduced so the changes that

[1] Approximately 4.5 percent of drug purchases linked to more than one therapeutic class and were assigned to a unique class using a combination of condition information and random assignment. About 1.0 percent of drug purchases could not be linked to Multum.

take place during the time period of our study do not diminish the policy relevance of the results.

In some specifications we use medical conditions as reported by household respondents to compare the predictive power of drug therapeutic categories against medical condition categories at similar levels of aggregation. Medical conditions in the MEPS are collected at various points during the interview. Respondents are asked if individuals in the household have any medical conditions at the beginning of each round of the survey. Additional medical conditions may be recorded whenever there is a medical event such as a visit to the doctor or hospital to explain the reason for the visit.

In order to minimize some of the differences between years of data, we adjust prescription drug expenditures using the consumer price index (CPI) for prescription drugs. By using this inflation adjuster we are capturing both general price inflation as well as prescription drug price inflation that reflects the higher prices of newly introduced drugs. For the purposes of this analysis, this adjustment factor is the most appropriate. Our purpose is to try to make the four years of data as similar as possible. At the same time, it should be noted that we include panel year dummy variables in all of our regressions to control for panel effects.

Results

In the following results, Tables 1 and 2 show how prescription drug expenditures differ from total and non-drug expenditures in terms of their concentration and persistence over time. These two aspects of the expenditure distribution have important implications for the design of efficient health insurance markets. Next, in Tables 3 and 4,

we present selected health status and socioeconomic characteristics of the Medicare population and subpopulations examined in this study. We also contrast the use of prescription drugs by common therapeutic classes and subclasses by subgroups of the Medicare population. In Tables 5 and 6, we present our regression models and compare their predictive power across various specifications and subgroups. Finally, in Table 7, we present relative risk ratios that show how certain groups of Medicare beneficiaries are much more expensive on average than others in terms of their predicted drug expenditures.

Prescription drug expenditures are not distributed evenly across the Medicare population and a large portion of aggregate expenditures is accounted for by a small percent of the population. In the top panel of Table 1, beneficiaries are ranked according to their prescription drug expenditures. We see that the top one percent accounts for 8.8 percent of all prescription drug expenditures and the top 10 percent of beneficiaries accounts for 40.3 percent. The median drug expenditure in our sample is $564 which is less than one-tenth the amount of the threshold estimate of $5,961 that identifies those in the top one percent of the distribution.

Prescription drug expenditures, however, are slightly less concentrated than non-drug and total expenditures. In the second panel of Table 1, we see that the top one percent of persons account for 17.3 percent of *non-drug* health expenditures while the top 10 percent of persons account for 62.1 percent of non-drug expenditures. The third panel of Table 1 shows that the top one percent of persons accounts for 14.7 percent of *total* health care expenditures while the top ten percent of persons accounts for 54.8 percent of total health expenditures. Non-drug and total health expenditure are more skewed than

drug expenditures because of rare, high cost events like extended hospitalizations.

The more concentrated or skewed the expenditure distribution the greater the potential for differences between low risk and high risk beneficiaries. A highly skewed distribution also means that a few high risk individuals can have a disproportionate impact on a plan's total costs. If risk adjusted payments don't fully account for some predictable expenditures by high health risk enrollees, then plans will have an incentive to discourage enrollment of certain high risk patients. Reinsurance provisions, however, can mitigate this potential problem.

Along with less concentration, prescription drug expenditures are also more persistent over time compared to non-drug and total health expenditures. In the top panel of Table 2 we see that among beneficiaries whose prescription drug expenditures placed them in the top five percent in year 1, 50.5 percent of them remained in the top five percent in year 2. In the bottom panel, however, we see that among beneficiaries whose total expenditures placed them in the top five percent in year 1, only 24.4 percent of them remained in the top five percent in year 2. Thus beneficiaries are more than twice as likely to have persistently high prescription drug expenditures as persistently high total health expenditures over a two year period. The more persistent are expenditures from one year to the next, the easier it is to predict which individuals will be high risk individuals for the plan. Adverse selection is more likely when there is greater degree of persistence of high expenditures over time.

Table 3 presents selected socioeconomic and health status characteristics for the total Medicare population as well as for policy relevant subgroups. These characteristics are based on "year one" information from the four pooled panels of MEPS data. In the

first column we see that our sample of beneficiaries (excluding those who died and were institutionalized) represents 34.3 million persons per year on average. About 13.4 percent of the population live below the poverty line while 25.0 percent live between 100 and 200 percent of poverty. About 39.0 percent of the population have employer sponsored private supplemental insurance coverage, while 18.2 percent hold private non-group coverage including Medigap plans, and 14.7 percent are covered by Medicaid or some other public insurance in addition to their Medicare.[2] More than one-third of beneficiaries report having fair or poor health.

In the second panel from the left of Table 3 we compare the characteristics of Medicare beneficiaries who are age 65 and older to the characteristics of those under 65. The population under age 65 qualifies for Medicare because of permanent disabilities.[3] The disabled Medicare population represents a potentially vulnerable subgroup that may have different prescription drug utilization patterns than the much larger aged population. Disabled Medicare beneficiaries are more likely to be Black and Hispanic than are aged beneficiaries. Nearly one-third (32.5 percent) of disabled beneficiaries live in poverty compared to 10.8 percent of the aged. More than twice as many disabled beneficiaries report having fair or poor health compared to aged beneficiaries (68.6 vs. 30.4 percent). Disabled beneficiaries are also more likely than the aged to have trouble with ADLs and IADLs (34.7 vs 13.6 percent). It is not surprising that 75.3 percent of the disabled versus 23.8 percent of the aged report activity limitations including limitation in the ability to

[2] The MEPS does not measure which Medicare beneficiaries hold Medicare HMO coverage. Beneficiaries without private or public supplemental coverage include those with FFS Medicare as well as those with Medicare HMOs.

[3] Disabled Medicare beneficiaries are classified as aged beneficiaries upon turning age 65. MEPS cannot identify persons who formerly held Medicare as a disabled beneficiary.

work, do housework, or attend school.

In the third panel across of Table 3 we compare Medicare subgroups by insurance status. Although insurance status is likely to change as the MMA takes full effect in 2006, persons who are currently enrolled in both Medicaid and Medicare also represent a potentially vulnerable subgroup. Their prescription drug coverage will become part of the total Medicare benefits they receive, rather than being covered by state Medicaid programs. More than one-third of the dually enrolled live in poverty (35.7 percent) compared to 5.9 percent of those with private group insurance. About 54.7 percent of the dually enrolled report fair or poor health status compared to 27.7 percent of those with private group insurance. Dually enrolled Medicare beneficiaries are also much more likely than those with private group insurance to have trouble with ADLs and IADLs, activity limitations, and difficult walking.

Table 4 shows how utilization of some common prescription drug therapeutic subclasses varies across subgroups of Medicare beneficiaries. Most of the selected therapeutic subclasses in the table ranked in the top 10 in purchases or expenditures among the Medicare population during the period 1997 to 2001. A couple of additional subclasses are included because of large and significant coefficients in our prediction models. Cardiovascular drugs are among the most commonly used drugs within the Medicare population. Among the full Medicare population shown in the first column, we find that on average during this four year period, 20.7 percent of the total community Medicare population purchased at least one prescription per year for calcium channel blockers, 19.5 percent a diuretic, 16.0 percent ACE inhibitors, and 15.4 percent a beta blocker. In addition to these anti-hypertensive medications, about 14.6 percent of all

Medicare beneficiaries purchased an anti-cholesterol drug. Several hormone drugs, anti-depressants, and analgesics were also purchased by more than 10 percent of the full Medicare population.

When we compare the aged and disabled Medicare populations in the second section of Table 4, however, differences emerge between the two groups. For instance the aged are more likely to use a cardiovascular drug than are the disabled. On the other hand, the disabled Medicare population is much more likely to use psychotherapeutic drugs than is the aged population. About 23.6 percent of the disabled purchased at least once prescription per year for an antidepressant during this four year time period compared to only 9.1 percent of the aged. Use of anti-psychotics was more than 5 times greater in the disabled population compared to the aged (10.5 vs 1.9 percent). Many of the disabled qualify for Medicare coverage because of severe mental illness. The disabled are also greater users of some analgesics and bronchiodilators.

There is a large degree of overlap between the disabled Medicare population and the dually enrolled Medicare and Medicaid population, so some of the patterns repeat themselves when we compare the dually enrolled to beneficiaries with private supplemental insurance, in the third section of Table 3. Use of anti-depressants, anti-psychotics, some analgesics and H2 antagonists is greater among the dually enrolled than among privately insured beneficiaries. Also, Medicare beneficiaries enrolled in Medicaid are more likely to use bronchiodilators and less likely to use sex hormones and thyroid drugs than are Medicare beneficiaries with private coverage. The use of cardiovascular drugs shows mixed patterns. Anti-cholesterol drugs and beta blockers are more common among those with private group insurance compared to those who are enrolled in

Medicaid and Medicare.

In Table 5, we present measures of R-square from several different regression models predicting prescription drug expenditures in year two based on information from year one. The models differ by the inclusion of different sets of independent variables. In the first column of Table 5, we predict expenditures for the total Medicare population. In the first row model 1 shows that using therapeutic class information by itself allows us to predict 25.9 percent of the variation in year two drug expenditures. Recall that therapeutic class information consists of dummy variables indicating whether there was any use within a set of 13 broadly defined classes of drugs. The R^2 for model 2 increases to 36.8 percent when we use the more detailed therapeutic subclass dummy variables which refer to 59 more narrowly defined drug categories. The aggregate and detailed prescription drug therapeutic categories are statistically significantly more powerful in predicting future drug expenditures than are the corresponding self reported medical conditions. For example, model 2 which contains therapeutic subclasses explains 36.8 percent of the variation compared to model 4 which contains self-reported medical conditions model and explains 26.5 percent of the variation ($p < .05$).

The comparison of drug therapeutic categories versus medical condition categories is slightly tilted in favor of the therapeutic categories since, by definition, information on therapeutic category is also an indicator of use of medical services. The drug therapeutic information doesn't exist unless a beneficiary has purchased a prescription. In many cases, purchasing a prescription often implies a prior medical visit as well. Household reported medical conditions, on the other hand, are not always associated with a concurrent medical event. Nonetheless, medical conditions provide a

useful point of reference in assessing the gain in prediction resulting from drug therapeutic information.

Model 5 which includes demographic and some health status measures has relatively little explanatory power (R^2 = 13.8). Using prior year drug expenditures as in model 6, on the other hand, increases the measure of R^2 to 42.8 percent. Yet, the standard error of the R^2 for model 6 is 7.6%, higher than for any of the other models. Since there is a lot of variation in prior year drug expenditures and this is the only variable in the model except for panel dummy variables, it is not surprising that the standard error is relatively high.

In the lower rows of Table 5 we combine sets of explanatory variables. Model 7 which combines demographic and drug therapeutic subclass variables explains more variance in year 2 expenditures (R^2 = 39.4) compared to model 8 which combines demographic and detailed medical condition variables (R^2 = 30.6).[4] The strongest specification is model 9, containing therapeutic subclass dummy variables, sociodemographic and health status measures, and year one's total prescription drug spending, which explains 52.6 percent of year two's drug expenditures.

These patterns are similar across all of the different subgroups whose expenditures we model. Although it is inappropriate to directly compare measures of R^2 across groups, we can compare the rankings of the models across groups.[5] In other words, for all subgroups the demographic variables explained the least amount of variation. Similarly, the drug therapeutic subclass model dominated the detailed medical

[4] Significant at the 10 percent level ($p < .10$)
[5] Differences in samples sizes of the subgroups can affect the measure of R2. With small samples, there is also a danger of overfitting the regression model. To avoid overfitting we dropped therapeutic subclasses that contained fewer than 15 persons.

conditions model, although the differences in R^2 for these two competing models were not statistically significant except for the full population and the 65 and over population. Across all subgroups except the privately insured, the model containing therapeutic subclass dummy variables, sociodemographic and health status measures plus year one's total expenditures on drugs explained more than half of the variation in year two drug expenditures.

Table 6 shows how much easier it is to predict drug expenditures than non-drug or total health expenditures in the Medicare population. Measures of R^2 are consistently much lower in the non-drug and total health expenditure models than in the drug expenditure models, reflecting the greater levels of persistence in drug expenditures from one year to the next. We also see that drug therapeutic subclass information works at least as well as detailed medical condition information in predicting non-drug and total health expenditures (differences in R^2 are not statistically significant).

In Table 7, we use the regression model 7 from Table 5 containing therapeutic subclass dummy variables plus sociodemographic and health status measures estimated on the entire Medicare population to generate relative risk scores. We compute the ratio of predicted year two expenditures divided by mean year two expenditures. Expressed as a percent, these relative risk scores indicate which groups of Medicare beneficiaries are predicted to have above or below average expenditures. Thus, the scores indicate which groups represent high or low risks to an insurance company selling stand alone PDPs. The scores also indicate which groups have the greatest demand for prescription drugs and are more likely to enroll in the voluntary plans when other alternatives are lacking or less generous.

We chose to measure predicted expenditures as a function of mean expenditures because the mean serves as a policy relevant benchmark against which to measure risk. If the PDPs were not subsidized by the government and community rating were mandated then premiums would be a function of the mean expense plus some loading factor. The highly skewed distribution of prescription drug expenditures, however, implies that the mean is greater than the median. In our data about 33.6 percent of the population spent more than the mean expense of $962, while the median person in the Medicare community population spent about $564. Expressed as a function of the mean, the median person would have a relative risk score of about 58.6 percent.[6] Thus, groups with an average relative risk score greater than 100 percent are high risk groups.

Table 7 shows that male and female beneficiaries under age 65 have a higher than average risk of using prescription drugs. Men under age 65 are predicted to spend 124.8 percent of mean expenditures while women under age 65 are predicted to spend 179.1 percent of the mean. Blacks and Hispanics are predicted to spend less relative to the mean compared to whites and others (93.6 and 91.4 vs 101.2 percent). These predictions hold insurance status constant using population means so that the relative risk scores would not reflect differences in current insurance status. It is interesting that poverty status by itself does not show much variation in relative risks. This may reflect the fact that not all Medicare beneficiaries who are eligible for Medicaid coverage are enrolled. Thus persons living in poverty include those with relatively generous Medicaid coverage as well as those without any supplemental coverage. On average they are not especially

[6] The full regression model used to predict the relative risk ratios is included in Appendix One. For the prediction of relative risk ratios we held the insurance parameters constant and used population averages. This eliminates variation in relative risk resulting from current insurance status which will likely change as the Medicare legislation is implemented in 2006.

high relative risk.

As expected health status signals large variations in relative risk. Persons reporting they are in fair or poor health have a relative risk score of 146.7 percent of the mean while those in very good or excellent health have a relative risk score of 57.5 percent. Similarly, persons reporting ADLs or IADLs have a relative risk of 149.8 percent while persons with activity limitations and difficulty walking have relative risks of 153.7 percent and 138.8 percent respectively.

Of particular interest, however, are the relative risks of persons who have used at least one prescription in the indicated therapeutic subclasses. Self-reported health status, disability status, and poverty status may not be easily measured by insurers but use of drugs by therapeutic categories will be readily available after one year's experience. Such information may also be available from firms' experiences with the Medicare discount drug program. As shown on the right hand side of Table 7, use of drugs in any of the listed categories raises the relative risk to more than 100 percent. Individuals prescribed anti-anginal agents or anti-psychotics are predicted to spend more than twice the mean expenditure, putting them into the very top of the distribution of drug expenditures. Individuals using proton pump inhibitors and anti-depressants are predicted to spend 197.9 and 196.3 percent of the mean, respectively. The use of ACE inhibitors, anti-cholesterol drugs, anti-diabetic agents, H2 antagonists, and bronchiodilators also raise relative risk scores to very high levels (173.6, 176.5, 186.7, 174.7, and 173.4 percents respectively). When the relative risk score is greater than 100 percent, it means not only that people in the group have high prescription drug expenditures in the current year but that they are also predicted to have high drug

expenditures next year, too.

Discussion

This study demonstrates how the MEPS data can support longitudinal analyses of the entire Medicare population including those with and without current prescription drug coverage. In addition, the inclusion of the National Drug Code allows us to link to a secondary data base containing information on prescription drug therapeutic classes and subclasses.[7] The MEPS small sample sizes remain a limitation, however, in terms of refining risk adjustment methodologies. The results of this study should be tested on larger Medicare datasets based on claims data.

In this paper we have shown that prescription drug expenditures are highly persistent over a two year period. About half of the variation in prescription drug expenditures can be predicted using information from the previous year, including therapeutic categories based on drug utilization. The high degree of persistence in prescription drug expenditures over time contrasts with the level of persistence in non-drug and total health expenditures, and implies that adverse selection is potentially a greater problem in markets for stand-alone prescription drug plans than in other health insurance markets.

In order to minimize the potential for adverse selection, the MMA requires the development of risk adjustment methodologies for PDPs. In this paper we also show that information on drug therapeutic categories can significantly increase the predictive power of regression models. Drug therapeutic categories are based on pharmacy claims and

[7] The NDC is not available in the Medicare Current Beneficiary Survey, the other large household survey database.

would be readily available to insurers making them a useful tool for risk adjustment methodologies.

This study also shows that users of certain drugs are more likely to have high predicted prescription drug costs compared to others. The implications of this predictability are two-fold. One, without adequate risk adjusted payments Medicare PDP insurers may have an incentive to discourage such groups from enrolling in their plans. Two, individuals in these groups may be more likely to enroll in Medicare PDPs if they do not have access to alternatives. In the short term insurers will not be put at much financial risk for their performance so adverse selection is not a major concern. It bears careful watching, however, since some of the most vulnerable Medicare beneficiaries use certain prescription drugs for the treatment of their chronic conditions that will mark them as high risk individuals.

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Table 1

Distributions of Expenditures (in 2000 Dollars) by Service: Non-Institutionalized Medicare Beneficiaries, 1996-2000

Percent of Medicare Population Ranked by Drug Expenditures	Expenditure Threshold	Percent of Total Dollars
Prescription Drug Expenditures		
Top 1 Percent	$5,961	8.8%
Top 5 Percent	3,269	25.9
Top 10 Percent	2,412	40.3
Top 25 Percent	1,295	67.5
Top 50 Percent	564	90.3
Mean Expenditure (st. error)	962 (22)	
Non-Drug Expenditures		
Top 1 Percent	$53,453	17.3%
Top 5 Percent	21,683	45.3
Top 10 Percent	11,749	62.1
Top 25 Percent	3,887	84.0
Top 50 Percent	1,127	95.7
Mean Expenditure (st. error)	4683 (165)	
Total Expenditures		
Top 1 Percent	$55,060	14.7%
Top 5 Percent	23,858	39.4
Top 10 Percent	13,445	54.8
Top 25 Percent	5,369	77.2
Top 50 Percent	2,144	92.3
Mean Expenditure (st. error)	5645 (171)	

Source: Authors' calculations from pooled MEPS data, 1996 through 2000.

Table 2

Persistence of Health Expenditures by Service: Non-Institutionalized Medicare Beneficiaries, 1996-2000

Year One Expend. Cat.	Year Two Expenditure Category			
	Top 5	Top 10	Top 25	Top 50
Prescription Drug Expenditures				
	percent distribution			
Top 5	50.5	72.8	89.8	97.3
Top 10	34.5	54.5	83.8	96.2
Top 25	17.7	33.6	66.8	91.9
Top 50	9.9	19.6	45.8	80.6
Non-Drug Expenditures				
	percent distribution			
Top 5	23.4	38.4	61.5	81.9
Top 10	18.0	31.7	57.2	81.8
Top 25	11.7	21.8	46.6	74.0
Top 50	7.7	14.7	35.7	66.4
Total Expenditures				
	percent distribution			
Top 5	24.4%	40.4	69.1	88.8
Top 10	18.2	31.4	60.9	86.8
Top 25	12.1	22.8	49.4	79.6
Top 50	8.2	15.8	38.5	71.7

Source: Authors' calculations from pooled MEPS data, 1996 through 2000.

Table 3

Socioeconomic and Health Status: Non-Institutionalized Medicare Beneficiaries, 1996-2000

		Age		Supplementary Insurance		
	Full Population	65 and Older	Less than 65	Private Group	Private Non-Group	Public
Total Population (millions)[1]	34.3	30.3	4.0	13.4	6.2	5.1
			Percent of Beneficiaries			
Age						
19 to 64	11.8%	0.0%	100.0%	8.1%**	2.9%**	29.1%**
65 to 74	50.2	57.0	0.0	59.4**	51.7	36.8**
75 and Older	38.0	43.0	0.0	32.5**	45.3**	34.0**
Gender						
Male	43.5	42.2	53.3*	48.8**	37.6**	38.4**
Race / Ethnicity						
Black	9.1	7.8	18.1*	6.5**	2.9**	19.0**
Hispanic	5.6	5.2	8.4*	2.8**	2.5**	15.3**
White and Other	85.4	86.9	73.5*	90.8**	94.6**	65.7**
Income as a Percentage of the Poverty Line						
Less than 100%	13.4	10.8	32.5*	5.9**	9.2**	35.7**
100 to 200%	25.0	24.6	27.9	17.6**	28.1**	33.1**
More than 200%	61.6	64.6	39.6*	76.5**	62.7	31.2**
Supplementary Insurance Status						
Private Group	39.0	40.6	26.6*	100.0	0.0	0.0
Private Non-Group	18.2	20.0	4.5*	0.0	100.0	0.0
Public	14.7	11.9	36.4*	0.0	0.0	100.0
No Supplement	28.1	27.6	32.4*	0.0	0.0	0.0
Marital Status						
Married	54.5	55.9	43.6*	69.8**	54.0	27.1**
Not Married	45.5	44.1	56.4*	30.2**	46.0	72.9**
Education						
Less than High School	34.5	34.0	38.3	24.6**	31.1**	55.6**
High School Grad	34.6	34.0	39.0*	36.9**	36.0	27.5**
Some College, or more	30.9	31.9	22.6*	38.5**	32.8	16.9**
Health Status						
Poor or Fair	34.9	30.4	68.6*	27.7**	30.5**	54.7**
Good	33.1	34.9	19.5*	34.7	32.4	27.1**
Very Good or Excellent	32.0	34.7	11.9*	37.6**	37.1**	18.2**
Disability Status						
IADL or ADL	16.1	13.6	34.7*	10.7**	12.8**	33.4**
Activity Limitation	29.9	23.8	75.3*	21.0**	23.5**	55.0**
Difficulty Walking	40.1	37.6	58.8*	33.9**	38.4	53.7**

Source: Authors' calculations from pooled MEPS data, 1996 through 2000

Note: 1. Average annual population from 1996-2000.

*The difference in estimates for the 65+ and < 65 populations is significant at the p < .05 level.

**The estimate for an insurance category is different from the full population at the p < .05 level.

Table 4

Percentage of Population Using Selected Therapeutic Subclasses of Drugs: by Age and Supplementary Insurance Status: Non-Institutionalized Medciare Beneficiaries, 1996-2000

Therapeutic Subclass	Full Population	Age		Supplementary Insurance		
		65 and Older	Less than 65	Private Group	Private Non-Group	Public
Total Population (millions)[1]	34.3	30.3	4.0	13.4	6.2	5.1
	percent of beneficiaries with at least one purchase					
Cardiovascular Drugs						
Calcium Channel Blockers	20.7%	21.3%	16.2%*	20.9%	19.1%	23.5%
ACE Inhibitors	16.0	16.5	12.6*	16.6	16.0	15.6
Diuretics	19.5	20.4	12.4*	18.5	21.8	20.7
Beta Blockers	15.4	15.8	11.6*	16.7**	15.2	11.8**
Antihypertensive Comb.	9.7	10.3	5.4*	9.1	11.4	9.0
Anti-Cholesterol (Statins)	14.6	15.0	11.4*	17.1**	15.6	11.0**
Anti-Anginal Agents	7.0	7.1	6.4	7.2	5.5	9.0**
Hormones						
Sex Hormones	14.1	13.9	15.1	17.2**	13.9	10.8**
Antidiabetic Agents	13.1	13.0	14.6	13.0	11.4	15.6**
Thyroid Drugs	10.4	10.8	7.0*	11.1	10.9	7.6**
Antineoplastics	3.6	3.6	2.9	3.7	4.3	3.3
Gastrointestinal Drugs						
H2 Antagonists	8.4	8.1	10.8*	8.7	7.5	12.1**
Proton Pump Inhibitors	6.7	6.4	9.0*	7.1	5.5	7.4
Psychotherapeutic Drugs						
Anti-Depressants	10.8	9.1	23.6*	9.9	10.2	15.8*
Anti-Psychotics	2.9	1.9	10.5*	2.1**	2.0**	7.0**
Analgesics						
NSAIDs	14.7	13.5	23.0*	15.3	11.6**	18.9**
COX-2 Inhibitors	1.6	1.6	1.9	1.6	1.5	2.8**
Respiratory Tract Drugs						
Bronchiodilators	6.5	5.9	10.4*	6.1	5.2	10.2**
Upper Respiratory Comb.	9.7	9.5	11.4	10.1	11.0	8.9

Source: Authors' calculations from pooled MEPS data, 1996-2000

Note:

1. Average annual population from 1996-2000.

*The difference in estimates for the 65+ and < 65 populations is significant at the $p < .05$ level.

**The estimate for a given insurance category is different from the estimate for the full population at the $p < .05$ level.

Table 5

Percentage of Year Two Drug Expenditures Explained by Year One Variables: Measures of R-Square by Model, Age and Supplementary Insurance Status: Non-Institutionalized Medicare Beneficiaries, 1996-2000

Variables Included in Model	Full Population	Age		Supplementary Insurance		
		65 and Older	Less than 65	Private Group	Private Non-Group	Public
1. Therapeutic Class (TC)	25.9	30.2	24.8	24.0	27.7	27.3
	(2.4)	(1.2)	(5.7)	(3.8)	(4.8)	(6.1)
2. Therapeutic Subclass (TSC)	36.8	42.1	40.4	36.5	46.2	39.9
	(3.3)	(2.2)	(10.1)	(6.3)	(7.1)	(9.4)
3. Aggregate Conditions (ACond)	18.3	22.3	17.3	17.9	23.1	17.1
	(1.7)	(1.1)	(4.3)	(2.5)	(3.4)	(5.2)
4. Detailed Conditions (DCond)	26.5	32.7	24.3	28.9	32.8	25.2
	(2.7)	(2.0)	(9.3)	(4.7)	(7.7)	(7.4)
5. Demographic (Dem)	13.8	16.0	12.8	15.1	22.2	16.1
	(1.6)	(1.2)	(8.4)	(3.3)	(5.9)	(5.1)
6. RX Expenditure (Year 1)	42.8	49.5	33.9	33.5	46.3	54.4
	(7.6)	(2.0)	(16.6)	(13.9)	(4.0)	(4.7)
7. TSC and Dem	39.4	44.7	44.8	40.0	51.7	44.8
	(3.5)	(2.4)	(12.6)	(7.2)	(8.6)	(10.3)
8. DCond and Dem	30.6	36.1	31.8	33.0	40.8	33.9
	(3.0)	(2.2)	(13.2)	(5.8)	(9.3)	(9.2)
9. TSC, Dem, and Year1	52.6	56.4	57.3	49.3	61.5	64.8
	(4.3)	(2.2)	(12.7)	(9.2)	(6.9)	(7.1)
10. DCond, Dem and Year1	50.5	55.3	51.8	46.4	57.8	63.6
	(5.0)	(2.1)	(14.6)	(9.7)	(7.0)	(6.4)
Sample Size	6826	5914	912	2412	1187	1305

Source: Authors' calculations from pooled MEPS data, 1996-2000

Note: Standard errors in parentheses estimated with balanced repeated replicates using 128 replicates

Table 6

Percentage of Year Two Health Expenditures Explained by Year One Variables: Measures of R-Square by Model and Type of Health Expenditure: Non-Institutionalized Medicare Beneficiaries, 1996-2000

Variables Included in Model	Drug Expenditures	Non-Drug Expenditures	Total Expenditures
		(standard errors)1	
1. Therapeutic Subclass (TSC)	36.8	9.1	12.1
	(3.3)	(2.1)	(2.0)
2. Detailed Conditions (DCond)	26.5	7.4	9.7
	(2.7)	(1.8)	(1.9)
3. TSC and Dem	39.4	12.5	15.5
	(3.5)	(2.8)	(2.9)
4. DCond and Dem	30.6	11.5	14.1
	(3.0)	(2.6)	(2.5)
5. TSC, Dem, and Year1[2]	52.6	15.4	18.6
	(4.3)	(3.5)	(3.3)
6. DCond, Dem and Year1[2]	50.5	15.0	18.1
	(5.0)	(3.3)	(3.1)
Sample Size	6826	6826	6826

Source: Authors' calculations from pooled MEPS data, 1996-2000

Notes:

1. Standard errors (in parentheses) are estimated using 128 balanced repeated replicates

2. Year one expenditures are defined as drug expenditures for the drug expenditure model. Year one expenditures are defined as two separate variables (drug and non-drug expenditures) for the non-drug expenditure and total expenditure models.

Table 7

Predicted Drug Expenditures as a Percentage of Mean Expense:[1]
by Selected Sub-Groups of the
Non-Institutionalized Medicare Population, 1997 to 2000

Demographic Characteristics		**Therapeutic Subclass**	
Age / Gender		**Cardiovascular Drugs**	
Less than 65, male	124.8%*	Calcium Channel Blockers	166.6%**
Less than 65, female	179.1**	ACE Inhibitors	173.6**
65-74, male	86.5**	Diuretics	163.3**
65-74, female	93.9*	Beta Blockers	149.5**
75 and older, male	90.8**	Antihypertensive Comb.	133.5**
75 and older, female	100.8	Anti-Cholesterol (Statins)	176.5**
Race / Ethnicity		Anti-Anginal Agents	205.3**
Black	93.6	**Hormones**	
Hispanic	91.4	Sex Hormones	136.1**
White and Other	101.2	Antidiabetic Agents	186.7**
Income as a Percentage of the Poverty Line		Thyroid Drugs	140.2**
Less than 100%	107.6	Antineoplastics	151.1**
100 to 200%	102.7	**Gastrointestinal Drugs**	
More than 200%	97.2	H2 Antagonists	174.7**
Health Status		Proton Pump Inhibitors	197.9**
Poor or Fair	146.7**	**Psychotherapeutic Drugs**	
Good	91.8**	Anti-Depressants	196.3**
Very Good or Excellent	57.5**	Anti-Psychotics	206.1**
Disability Status		**Analgesics**	
ADL or IADL	149.8**	NSAIDs	132.1**
Activity Limitations	153.7**	COX-2 Inhibitors	159.7**
Difficulty Walking	138.8**	**Respiratory Tract Drugs**	
Total Prior Drug Use		Bronchiodilators	173.4**
No Drug Purchases in Year1	10.1**	Upper Respiratory Comb.	109.9**

Source: Authors' calculations from pooled MEPS data, 1997-2000

Notes:

* p < .10, ** p < .05 that estimate is different from 100%.

1. Expenditures are predicted with a model that includes therapeutic subclass and demographic variables. Coefficients for this model are given in Appendix One.

Appendix One

Regression Coefficients: Association of Year One Therapeutic Subclass and Demographic Variables with Year Two Drug Expenditures

Therapeutic Subclass Variables	Coefficient	Therapeutic Subclass Variables	Coefficient
Antimalarial Agents	-$161	Antirheumatics	319*
Cephalosporins	-44	Antigout Agents	96
Macrolides	11	Fibric Acid Derivatives	374*
Miscellaneous Antibiotics	-126	Nasal Preparations	217
Penicillins	65	Antidepressants	446*
Quinolones	-52	Antipsychotics	725*
Sulfonamides	170	Proton Pump Inhibitor	456*
Tetracyclines	-43	COX-2 Inhibitors	161
Antineoplastics	363*	**Demographic Variables**	
ACE Inhibitors	363*	Less than 65, male	266
Antidadrenergic Agents (Peri.)	340*	Less than 65, female	492*
Antidadrenergic Agents (Cent.)	295*	65-74, male	73*
Antianginal Agents	254*	65-74, female	53
Beta Blockers	205*	Black	-173*
Calcium Channel Blockers	399*	Hispanic	-178*
Diuretics	131*	High School Grad	25
Inotropic Agents	-50	Some College	16
Antihypertensive Comb.	245*	College Degree	58
Miscellaneous Analgesics	153	Advanced Degree	219*
Narcotic Analgesics	100	Married	116
NSAIDs	67	Widowed	154
Salicylates	-84	Divorced/Seperated	72
Anticonvulsants	156*	Employed	-8.6
Antiemetic/Antivertigo	-18	Private Group Insurance	25
Antiparkinson	146	Public Insurance	74
Anxiolytics/Sedatives/Hyp.	100	Private Non-Group Ins.	-15
Muscle Relaxants	126	Income 100-199% Pov. Ln.	25
Anticoagulants	277*	Income 200-399% Pov. Ln.	54.9
Antiplatelet Agents	331*	Income 400% or more	-28.1
Anticholinergics/Antispas.	-171	Good Health	60
GI Stimulants	161	Fair Health	141*
H2 Antagonists	273*	Poor Health	216*
Laxatives	-201	Good Mental Health	-19
Adrenal Cortical Steroids	450*	Fair Mental Health	-98
Antidiabetic Agents	497*	Poor Mental Health	18
Sex Hormones	157*	IADL	-53
Thyroid Drugs	148*	ADL	87
Genitourinary Tract Agents	656*	Activity Limitation	162*
Iron Products	390*	Difficulty Walking	69
Mineral and Electrolytes	271*	Rural Northeast	107
Vitamins	194	MSA Northeast	75

Appendix One: Continuued

Regression Coefficients: Association of Year One Therapeutic Subclass and Demographic Variables with Year Two Drug Expenditures

Therapeutic Subclass Variables	Coefficient	Therapeutic Subclass Variables	Coefficient
Vitamins and Mineral Comb.	59	Rural Midwest	100
Antihistamines	70	MSA Midwest	162*
Bronchiodilators	279*	Rural South	62
Respiratory Inhalants	30	MSA South	28
Upper Respiratory Comb.	-151*	MSA West	-34
Dermatological Agents	-21	Panel1	-59
Opthalmic Preparations	148*	Panel2	-40
Anticholesterol (Statins)	495*	Panel 3	76
Narcotic Analgesic Comb.	-13		
Number of Obs.	6826	**R-Square**	0.394

Source: Authors' calculations from pooled MEPS data, 1997-2000

* indicates $p < .05$