NORC
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Continuation of Drug Risk Adjustment

Final Report

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Executive Summary

The Medicare Prescription Drug, Improvement, and Modernization Act of 2003 (MMA) includes a number of provisions directing that payments to plans incorporate an assessment of risk. Prospective risk adjustment involves assessment of expected future health care costs (in this case, expenditures on outpatient prescription drugs) for individual beneficiaries and then aggregation across a beneficiary population such as a plan. The MMA requires that CMS risk adjust each plan bid to account for differences across plans in enrollee health status. Risk-adjusted plan bids (from both PDPs and MAs) are used to establish a national benchmark—created by aggregating across all bids. Beneficiaries' premiums are then calculated based on the difference between the plan bid in which the beneficiary is enrolled and the national benchmark. An accurate risk adjustment process is critical from the Medicare program's perspective--in terms of fairly paying plans for the services delivered, allocating funds equitably between private plan beneficiaries and beneficiaries in traditional Medicare, and still maintaining appropriate incentives for plans.

This task order continues work that NORC previously conducted under contract to ASPE and related to assessment and refinement of the drug risk adjustment model to be used for implementation of the new Medicare drug benefit. In the previous project, NORC and its subcontractors—Georgetown University, IMS Health, and Direct Research—completed three sets of analyses. Task 1 assessed the range of potentially useful data sets for the implementation of a Part D risk adjustment model, and assessed and refined the specification of the CMS risk adjustment model. Task 2 conducted basic analyses of geographic variation in retail drug prices, pharmacy acquisition prices, and beneficiary spending on prescription drugs. Task 3 examined the risk-limiting mechanisms that are part of the MMA with an emphasis on two aspects of these mechanisms--the MMA language itself and the effectiveness of these factors in limiting plans' financial risks. In addition, under a modification to the initial contract, a linked Medicare-Medicaid data set was purchased and analyses of the dual eligible population were conducted.

A second project was developed to assist ASPE as the drug risk adjustment model continues to be refined and the drug benefit is implemented. In addition to Task 1 which focused on project management, analyses were structured around three main analytic tasks:

- Task 2: assess model and payment adequacy for low income and institutionalized beneficiaries
- Task 3: review inclusion of prior drug use or spending in risk adjustment model.
- Task 4: analyze regional variation in drug plan premiums and drug spending by Medicare beneficiaries

In addition, three smaller tasks involved reviewing data requirements for plan reporting to CMS and making recommendations on data to be collected to monitor implementation (Task 5), additional exploration of data sets to be used in assessing the risk adjustment model (Task 6), and preparation of brief papers from the initial project for the ASPE website (Task 7). A brief report related to Task 5 has been submitted under separate cover. The technical approach to each of the three main tasks and highlights of the findings are described briefly here.

Task 2: Analyze Adjustments for Low-Income and Institutionalized Populations

Underlying the accuracy of any risk adjustment methodology are the data used to make that adjustment. Task 2 was designed to develop data sources to examine the appropriateness of a) the structure of CMS risk adjustment model; b) the current payments based on model estimates; and c) the adjustments for institutionalized populations and *ex post* adjustment for low income populations.

We first applied a common set of drug prices to the two data sets being used—the Blue Cross Blue Shield Federal Employees Program (BCBS FEP) data and a linked Medicaid-Medicare data file. Using the combined data set, we then tested whether the linear risk adjustment model adopted by CMS was the appropriate specification or whether a model allowing interactions would be a better fit. In order to do the test, we calculated projected spending for each person based on the estimated model parameters from the CMS model. For three subgroups – Medicaid; institutionalized; and combined Medicaid-institutionalized–we then regressed the difference between actual and predicted spending (the residuals) against the same set of explanatory variables that is in the risk adjustment model. Finally, to examine whether reimbursements to insurance plans for enrolling Medicaid beneficiaries are adequate, we calculated the predictive ratio for the Medicaid population using the CMS model. We further modified the CMS model by adding a Medicaid indicator estimate of how much more (or less) a plan needs to reimburse a Medicaid beneficiary relative to a non-Medicaid beneficiary with the same diagnoses and of the same age and gender.

Key findings from this task include:

- The relationship between drug spending and patient characteristics is different for studied subgroups (Medicaid, institutionalized, and combined Medicaid and institutionalized). In our residual regressions, over one-third of age-sex dummies and over one-third of diagnoses were estimated to be statistically significant and coefficients for some diagnostic conditions were 10% of mean spending or larger for all three subgroups.
- The current risk adjustment model creates payments that are too low for some population subgroups such as institutionalized Medicaid recipients and some Medicaid recipients or institutionalized individuals with certain diagnoses, but too high for others such as institutionalized people who are not on Medicaid.
- The CMS model slightly underpays (by 3%) plans for enrolling Medicaid beneficiaries, but the ex-post low-income adjustment sufficiently compensates for the underpayment.
- The ex-post low-income adjustment is lower than the estimate of the spending difference between Medicaid and non-Medicaid beneficiaries but the adjustment is appropriate given that it is applied to values based on model estimates that include Medicaid beneficiaries. In other words, part of the spending difference is already incorporated into the base estimates.

Findings from this task indicate that there are missing interaction terms between Medicaid and institutionalized status and some diagnostic condition categories and patients' age and sex from the linear model. From a policy perspective, this might result in under-payment for specific population sub-groups (and over-payment for others). The under-payment is of particular policy concern because plans might undertake strategies to avoid enrolling such beneficiaries, creating a problem

with respect to access to the prescription drug benefit. Medicaid beneficiaries could potentially be singled out by insurance plans due to underpayment. However, our analysis of the appropriateness of the Part D reimbursement to insurance plans suggests that ex-post low-income subsidy adjustments sufficiently compensate plans for enrolling Medicaid beneficiaries.

Task 3: Analysis of Incorporating Lagged Drug Use into Risk Adjustment Models

The purpose of Task 3 was to explore the inclusion of data from actual drug claims (e.g., lagged drug spending or use) in the drug risk adjustment model. With respect to either spending or use, the focus of this task is on incorporating information from drug claims into a *diagnosis-based* risk adjustment model, rather than on developing a model that depends solely on prior drug use or spending to establish payment. Using the 1997-2001 Cost and Use files from the Medicare Current Beneficiary Survey (MCBS) and the most recent CMS prescription drug risk adjustment model, we updated empirical work that was previously conducted for ASPE that incorporated past drug spending into different risk adjustment models. We further expanded this analysis to explore incorporation of a limited amount of information on *drug utilization* rather than spending. To capture prior use, either individual drugs or drugs grouped into therapeutic categories were entered into the models. Three different measures (whether a person had any prescription, or one prescription, or 2 or more prescriptions) were constructed for each drug or drug category. The approach was to investigate some prior use models by running variations of the basic model and comparing them to a model based on prior year drug spending.

Our main findings include:

- There is not much difference in the prior use model between different measures (any prescription, 1 prescription, 2 or more prescriptions) when the number of drugs in the model is held constant.
- Prior use explains less than prior spending until the number of drugs/drug categories included in the model is high. For example, the model using individual drugs approaches the explanatory power of the prior spending model only when 500 to 1000 drugs are allowed to enter separately into the model.
- Simply counting the number of prescriptions appears to do about as well as separately categorizing the top 100 drugs.
- Prior spending and prior use predict differently for high and low spenders. The prior use models, in contrast with the prior spending models, grossly under-predict for the costliest patients, and over-predict for low-cost beneficiaries unless a very large number of drug categories is included in the regression.

Our results indicate that the inclusion of prior *use* rather than prior *spending* produces models that are significantly different and more appealing from a policy perspective. Use of lagged spending as a risk adjuster substantially weakens incentives for price competition and efficiency. In contrast, models with a modest number of drug categories (prior *use*) have lower explanatory power than the prior spending model, and generate predicted values that are only modestly well correlated with the predictions from the prior spending model. It does not seem to matter much whether the presence

of drugs was included based on a single prescription, multiple prescriptions, or a count of the number of prescriptions within the drug category. Thus, developers of a drug risk adjustment model incorporating some elements of prior use would have significant latitude to choose the method that gave the best combination of incentives and robustness toward variations in data reporting or variations in practice patterns. Under circumstances where there is missing diagnostic data AND the link between diagnosis and drug use is very strong, a hybrid model making use of both diagnostic information and some prior use provides less of an adverse incentive effect and some advantages.

Task 4: Analysis of Geographic Differences in Drug Use and Pricing

The purpose of this component of the project was to analyze geographic variation in beneficiary spending to determine whether some further adjustment to Medicare prescription drug plan payments may be necessary beyond the risk adjusters. The analysis relies on claims data for Medicare beneficiaries age 65 and over included in Blue Cross/Blue Shield's Federal Employee Plan (FEP) for 2002.

Highlights of the findings include:

- There is significant variation across regions in prescription drug expenditures per beneficiary. Spending ranged from $1,528 per person in Alaska (15% below the national average) to $2,011 per person in Georgia (12% above the national average) in 2002. This variation is a result both of variation in the amount of drugs that FEP enrollees use, and in the cost of the drugs they use.

- There is much more variation in days' supply per user than in the number of users, and this measure is closely correlated with overall spending (r=.88). The median number of days of medication supplied per person ranges from a low of 945 days' supply in Hawaii (13% below the national average) to a high of 1195 days' supply in the region that includes Indiana and Kentucky (10% above the national average).

- We also find variation in the cost for a day's supply of a prescription. The median cost of a day's supply ranges from $1.32 in Wisconsin (11% below the unweighted national average) to $1.60 in Alaska and South Carolina (7% above the national average). The variation in cost per day supplied is almost entirely a result of variation in the generic dispensing rate across regions. Further work is needed to understand whether variation in the generic dispensing rate is primarily a result of variation in the extent to which on-patent drugs with no generic substitute are prescribed, or variation in the extent to which generic substitutes are used when they are available. There is not significant variation in the prices consumers pay for the same prescriptions in different regions.

- There is even more variation in utilization of individual classes of drugs than in overall drug utilization. It appears that the variation in use of some classes of drugs may also be contributing to variation in spending, but because utilization of some classes is unrelated or even negatively correlated, some of the differences cancel each other out. The failure

of our explanatory models to clearly explain variation in use of these individual drug classes raises the possibility that there are unmeasured factors at work. One likely possibility is that regional physician prescribing patterns vary by class of drug, rather than favoring high or low utilization across all drugs.

- We also explore within-region variations in spending between metropolitan and non-metropolitan areas. Looking at spending and utilization within regions, we find that nationally, there is not a large difference between urban and rural spending for prescription drugs. Some individual regions have a notable difference between urban and rural utilization and spending, but the pattern is not consistent enough nationwide to make metropolitan status a promising basis for fine-tuning payments to prescription drug plans.

Our results, while finding substantial variation in prescription drug use and spending across regions, do not lead to a clear conclusion for making further adjustments to the federal payments to drug plans. Part D plans are varying their premiums from region to region. While this is probably due in part to market competition factors, such as the degree of competition from Medicare Advantage plans, it may also be indication that these plans expect some continued geographic variation in utilization. Ideally, utilization data from Part D plans can be used to study these questions further before the Department must submit its findings to Congress in 2009.

Chapter 1

CONTINUATION OF DRUG RISK ADJUSTMENT

Task 2: Analyze Adjustments for Low-Income and Institutionalized Populations

Purpose and Overview of Findings

The purpose of this task was to conduct additional analyses on the adjustments to be made in paying plans for the low-income and institutionalized populations under Medicare Part D. The results of these analyses could be used to confirm and/or refine the adjustments that have been recommended by CMS. However, since it may be impractical politically and/or logistically to modify the drug risk adjustment model at this time, the primary purpose of findings from this task is to illuminate for ASPE which subgroups might require special monitoring of access to plans and/or drugs, given the potential for under-payment.

In order to do this, the following basic steps were taken. First, we applied a common set of drug prices to the two data sets being used—the Blue Cross Blue Shield Federal Employees Program (BCBS FEP) data and a linked Medicaid-Medicare data file. Once the prices were selected and merged onto the data sets, the two data sets were combined and treated as one. Using the combined data set, we tested whether the linear risk adjustment model was the appropriate specification or whether a model allowing interactions would be a better fit. Our statistical tests indicate that there are missing interaction terms from the linear model. From a policy perspective, this might result in under-payment for specific population sub-groups (and over-payment for others). The under-payment is of particular policy concern because plans might undertake strategies to avoid enrolling such beneficiaries, creating a problem with respect to access to the prescription drug benefit. Specific subgroups--by demographics and conditions--that might be subject to under-payment are highlighted in the report. In particular, our analysis suggests that the use of a single amount to adjust for institutionalized status leads to an adjustment that is too small for those who are also on Medicaid and too large for those who are not.

Background

In anticipation of the implementation of the new Medicare Part D prescription drug benefit, during 2005 CMS developed a drug risk adjustment model for the payment of prescription drug plans. The purpose of the drug risk adjustment model is to ensure that payments to plans for prescription drugs

used by Medicare beneficiaries are equitable, by accounting for known differences in health status of the enrollees served.

The drug risk adjustment model developed by CMS was based on the Hierarchical Condition Category (HCC) model used for risk adjustment for all medical services. For use in paying for the new Part D prescription drug benefit, the model was modified by changing the specific conditions included in the model and by estimating new weights for those conditions. In developing the model, CMS paid particular attention to the payments to plans for certain special populations, most notably low-income persons and those residing in institutions.

Because no drug claims were available for the entire Medicare population, the model was developed using claims for federal retirees from the Blue Cross Blue Shield Federal Employee Program (FEP). There was concern from the outset that persons with FEP coverage are different than the Medicare population overall in a number of ways that might affect their use of prescription drugs. For example, persons who have worked for and retired from the federal government tend to be concentrated in certain geographic areas, have more generous benefits than other privately insured, and are potentially somewhat better educated and more well off than the overall Medicare population. In the earlier phase of this project, we tested the risk adjustment model on a number of different groups (including Medicaid enrollees, and institutionalized beneficiaries), and compared actual drug expenditures to predicted expenditures to see if the model would be likely to over-pay or under-pay for these populations. In fact, adjustments were included by CMS to compensate plans for the poorer health status not captured by the hierarchical conditions in the model and the likely higher use of prescription drugs by low-income and institutionalized populations.

The structure of the CMS model assumes that there is a fixed, constant difference in spending for certain subgroups of beneficiaries, such as those with low incomes and those who reside in nursing homes. The current model is based on estimates of an average difference in spending for these subgroups that is then added (or subtracted) for people in these subgroups. An alternative approach or structure for the model would be to allow the adjustments for the various disease and sex-age groups to differ depending on whether or not the beneficiary is in one of these subgroups. In other words, one might conjecture that the effect on drug spending of a particular condition is different for an institutionalized beneficiary than for a community-dwelling beneficiary and that this 'difference' might vary for different demographic subgroups. Under this alternative, the model would include interaction terms for these subgroups. The extreme case in which all model variables are interacted with subgroup indicators is equivalent to estimating different models for each subgroup.

In the remaining sections of this report, we describe the exploration of the data sets, the approach taken to combining the two data sets into one file, and the subsequent analyses of the risk adjustment model using the combined file.

Approach—Analysis of BCBS FEP and linked Medicaid-Medicare data

As mentioned above, most of the initial work conducted by CMS was done using the BCBS FEP data. At the later stages of development, a linked Medicaid-Medicare data set was obtained by ASPE and shared with CMS. These two data sets were combined for some of the final analyses; however, time was limited and some issues encountered with respect to differing prices across the two data sets made combining the data sets difficult.

Thus, one of the initial tasks for this project was to explore alternative approaches to combining the two data sets in order to represent the Medicare population more fully. Once we were able to combine the two different data sets into one with a common set of prices, the data set could be used to further explore the CMS risk adjustment model.

The concern about prices stemmed from the following: if the amounts paid by Medicaid for certain drugs were different than what BCBS paid, then the coefficients in the model would differ for people/conditions in a way that was not reflective of the relationship between health status and spending. Thus, several steps were taken prior to combining the two data sets. First, as part of this effort, we discussed with CMS staff the work that they had done on the claims files in order to try to combine the two data sets, and their assessment of data quality. We also obtained the additional quantity data that CMS received from BCBS toward the end of the last project in order to conduct our own analyses of the data quality. Finally, we contacted representatives from the Blue Cross Blue Shield Association in order to clarify several issues related to price variable definitions.

Analyses of BCBS Data. The BCBS FEP data comprises two files—(i) a person-level file with a total drug expenditure variable created by BCBS prior to their transmission of the data and (ii) a drug claim-level file with multiple claims per person—each claim includes a dollar amount on each individual claim. (This latter claim-level file was received from BCBS by CMS only at the very end of the initial project.) Using the 2003 BCBS data, NORC compared total expenditures in the person-level file and the total expenditure variable derived from summing the amounts on each claim in the claims file as follows:

1) For each claim in the claim-level file, total spending was calculated by multiplying unit price by number of metric units;

2) All claims for a given person were summed to calculate total spending by person (referred to as 'derived' spending);

3) The percentage difference between the two total spending variables was calculated as follows: derived total person-level expenditures (Derived $) minus reported total person-level expenditures (Person $) divided by reported total person-level expenditures

$$\frac{\text{(Derived \$)} - \text{(Person \$)}}{\text{Person \$}}$$

The mean of the percentage difference was 46 percent and median was 34 percent, indicating substantial difference between these two drug spending estimates and necessitating clarification with BCBS as to what these variables represented. In talking to a BCBS representative, we were told that the claim-level variable or what we refer to in summed form as the derived total expenditure variable is AWP (average wholesale price, or the undiscounted amount). The other (the total on the person-level file) represents the summed retail amounts, with the difference between the two being the retail discount and the dispensing fee (for retail only, not applicable for mail order).

Assigning Price Data. Following these discussions and analyses, a decision was made to move forward in applying a common pricing structure to combine the FEP and Medicaid-Medicare data so that we could conduct analyses of low-income and institutionalized populations. We identified the RedBook (Select format, obtained in early 2005 as part of the first project) as a source of secondary data that includes drug-level information on AWP.

We used prices from the RedBook to corroborate the FEP prices. First, we had to identify a set of NDC codes common to the different files. To do this, the first step was to subset the FEP claims to unique NDC codes; where there was more than one price for a given NDC, we picked a price for each NDC code randomly. (Variation in prices for a given NDC was small.) These unique NDCs were merged with the Redbook data, resulting in 21,385 NDC codes present in both files. We compared prices across the two files by calculating the Pearson product-moment, Spearman rank-order, and Kendall's Tau b correlation coefficients between the FEP price and the Redbook price (paired by NDC code). The coefficients were 0.785, 0.988, and 0.962 respectively, indicating a high degree of correlation.

Another check on comparability between prices in the two data sets was to check the distribution of the difference between the prices from the two files, by NDC. This was defined as— (Redbook price-FEP price)/FEP price. The median of this ratio is zero and both the 25 and 75 percentiles are close to zero. Based on these findings, we conclude that FEP prices are close to AWP prices. Given this conclusion, FEP prices by NDC were retained in the FEP file and merged onto the Medicaid-Medicare file. Thus, all expenditures in the final analysis file are based on AWP prices reported in FEP data and drug units reported in FEP and Medicaid, respectively. These expenditures were inflated to 2006.

Analysis of Risk Adjustment for Sub-Populations. The newly-developed file creates an opportunity to review the risk adjustment model using a common data set. Instead of developing estimates for certain subpopulations from different data sources or models than those estimated for other beneficiaries, we can now estimate a single model with the necessary parameters from a more heterogeneous population. These estimates will provide some information on whether differences in drug spending between subgroups varies across diagnoses or sex-age groups.

Thus, using these data, we estimated the CMS drug risk adjustment model, both in the form used by CMS and modified to include dummy variables for Medicaid (as a proxy for low income) and

institutionalized status. To assess the CMS model, we examined estimates from this model, its fitted values, and the residual values when actual spending is subtracted from estimated spending.

After estimating the model, we calculated projected spending for each person based on the estimated model parameters. For three subgroups – Medicaid; institutionalized; and combined Medicaid-institutionalized–we regressed the difference between actual and predicted spending (the residuals) against the same set of explanatory variables that is in the risk adjustment model.

The purpose of regressing the residuals on the explanatory variables from the risk adjustment model is to explore whether there are missing interactions related to the low-income and institutionalized populations.[1] If the relationships among the explanatory variables are the same for each studied subgroup as they are for the total population, this residual regression would be the equivalent of regressing a series of random numbers against the explanatory variables, with an expected r-squared of 0 and no coefficients that are statistically different from 0. In fact, the three residual regressions we ran resulted in statistically significant coefficient estimates and r-squareds between 0.02 and 0.07. For all three groups – Medicaid, institutionalized, and combined Medicaid-institutionalized – at least one third of the 15 age-sex dummies were statistically significant in these residual regressions. Although the parameter estimates were relatively small in magnitude for the Medicaid and Medicaid/institutionalized subgroups, they were quite large for the institutionalized group.

In addition, there is a specific test of whether interaction effects have been omitted from a model. The Pregibon Link Test explicitly tests whether a model was appropriately modeled as linear by regressing the original outcome variable (in this case drug spending) against the fitted values and the square of the fitted values from the model. If the coefficient estimate on the squared term is statistically significant, we can reject the hypothesis that the model is linear, the assumption underlying CMS's approach. Estimates from the Pregibon Link Test lead to a statistically significant estimate (with t-value over 100) on the squared predicted values, suggesting that there are interaction terms omitted from the model.

Combined, the Pregibon test and the residual regressions suggest that, from a statistical modeling perspective, it may be important to interact low-income and institutionalized status with the sex-age dummies and some disease dummies. What these do not help us understand, however, is whether such statistical improvements would lead to changes in payments that are important from a practical perspective (i.e., that they would make a difference with respect to plan payment that would impact plan incentives in a way that changes behavior).

To examine whether there appear to be important differences in predicted spending relative to actual spending for Medicaid and institutionalized individuals, we calculated the predicted ratio for the various age-sex groups, categorized with regard to Medicaid and institutionalization status. In

[1] The baseline regression used for this analysis replicates the CMS risk adjustment model with one modest adjustment – it includes an intercept and omits one sex-age dummy. This minor change to the model facilitated the residual analysis described here. The r-squared for this model is 0.25.

essence, the predicted ratio indicates how the payments predicted by the model compare to actual payments for the people in the category – if a plan happened to enroll individuals entirely within that category, the predicted ratio captures how the plan's payments would compare to actual spending. So, for example, the predicated ratio for women over 95 who are neither on Medicaid nor institutionalized is 0.965, suggesting that for this group of people, predicted payments are about 3.5 percent less than actual payments. (Table 1) Overall, the predicted ratios suggest that payments for the institutionalized, non-Medicaid group are over 11 percent larger than actual spending while those for institutionalized, Medicaid group are about 4 percent too small.

Table 1: Predicted Ratio of Drug Spending, Sex-Age Groups by Medicaid and Institutionalized Status

	Medicaid			
	NO		YES	
	Not Institutionalized	Institutionalized	Not Institutionalized	Institutionalized
Women:				
Under 64	--	--	1.005	0.938
65-69	1.003	1.195	0.984	0.917
70-74	1.000	1.141	1.008	0.930
75-79	0.997	1.157	1.023	0.966
80-84	0.997	1.139	1.013	0.993
85-89	0.996	1.094	1.012	0.988
90-94	0.990	1.109	1.007	1.004
Over 94	0.969	1.106	1.007	1.034
Men:				
Under 64	--	--	1.014	0.889
65-69	1.003	1.059	0.981	0.908
70-74	0.999	1.150	1.027	0.914
75-79	0.998	1.177	1.029	0.940
80-84	0.998	1.117	1.028	0.942
85-89	0.998	1.056	1.038	0.961
90-94	0.997	1.020	1.031	0.991
Over 94	1.011	0.947	0.982	0.991
ALL	0.999	1.116	1.009	0.959

Note: Predicted ratio is the ratio of the average predicted spending to average actual spending.

Table 2 presents estimates for different conditions included in the risk adjustment model. We present coefficient estimates as a percent of mean unadjusted spending for persons with that

condition. Again, this provides an indication of the relative size of the potential over- or under-payment. These estimates are shown for four different models—the risk adjustment model run on the entire population (the baseline model), and three residual models, one for the Medicaid population, one for the institutionalized population, and one for the combined Medicaid-institutionalized population.

Over one-third of the condition indicator coefficient estimates were statistically significant in each of the three residual subgroup regressions. While this suggests that these conditions, in particular, may be inappropriately specified, operationally, statistical significance is not of particular importance, since the baseline estimate for each condition is used to establish payments, regardless of its statistical significance. For our purposes, therefore, it is more important to determine whether any of the coefficients are large relative to drug spending for persons with that condition. To determine this, as noted above, we compared the baseline and residual subgroup regression coefficients for each condition to the mean unadjusted spending for everyone with that condition.

The coefficient estimates on the condition indicator variables show how much mean spending among people in the subgroup with the condition differs from the mean effect as estimated in the baseline regression. If this marginal effect is positive, it suggests that the baseline model under-adjusts costs associated with that condition for those in the subgroup (resulting in a payment that is too low). Conversely, if this marginal effect is negative, the opposite is true, with the baseline model overpaying for those in the subgroup.

For the conditions shown in Table 2, the coefficient estimate in at least one of the three residual subgroup regressions was at least 10 percent of mean spending, suggesting that the size of the potential under- or over-payment may be of concern. For example, the baseline coefficient estimate for HIV/AIDS is about half of total spending for all people with HIV/AIDS. The residual regressions suggest that for those who have HIV/AIDS and are institutionalized and for those with HIV/AIDS who are institutionalized and on Medicaid, this adjustment is too large.

These estimates suggest that the baseline model underpays for Medicaid recipients with diabetes with renal or circulatory symptoms, multiple sclerosis, hypertensive heart and renal disease, and cystic fibrosis; for institutionalized patients with muscular dystrophy; and for Medicaid, institutionalized patients with diabetes with renal or circulatory symptoms, multiple sclerosis, and cystic fibrosis. This implies that the baseline adjustments, while too small for these groups and disease, are too large for those outside these groups.

Conversely, according to these estimates there are some diseases for which the baseline estimates result in overpayment for those in these subgroups (and, implicitly, underpayment for those outside the group), namely hypertension among Medicaid recipients and institutionalized Medicaid patients and ten conditions for the institutionalized subgroup.

Table 2: Conditions for Which Subgroup Effects Differ from Mean Spending by 10% or More

	Coefficient estimate as percentage of mean unadjusted spending for patients with condition			
		Residual Regression for Subgroup:		
Condition:	**Baseline Model**	**Medicaid**	**Institutional**	**Medicaid & Institutional**
HIV/AIDS	51.63%	7.68%	-34.44%	-7.14%
Diabetes with Renal or Peripheral Circulatory Manifestation	7.42%	11.22%	4.92%	10.54%
Extensive Third-Degree Burn	5.93%	5.77%	-11.92%	5.18%
Mild Mental Retardation, Autism, Down's Syndrome	2.11%	0.00%	-11.10%	-0.12%
Attention Deficit Disorder	8.51%	1.81%	-12.44%	1.52%
Quadriplegia, Other Extensive Paralysis	3.02%	-1.51%	-11.38%	0.80%
Muscular Dystrophy	1.62%	-0.58%	16.69%	0.28%
Multiple Sclerosis	16.25%	14.38%	-12.48%	11.97%
Coronary Atherosclerosis/Other Chronic Ischemic Heart Disease	10.83%	-7.49%	-14.82%	-9.20%
Hypertensive Heart and Renal Disease or Encephalopathy	-0.51%	11.78%	5.77%	8.54%
Hypertension	16.63%	-14.56%	-10.40%	-11.56%
Cystic Fibrosis	5.39%	22.53%	-28.15%	19.12%
Kidney Transplant Status	15.06%	4.18%	-28.88%	-3.65%
Severe Head Injury	-8.19%	3.67%	-24.62%	-4.67%

Note: Orange shading indicates that residual regression suggests additional payment above baseline of 10% or more of mean spending; yellow shading suggestions that the baseline payment is too high by 10% or more of mean spending.

Examining the appropriateness of low-income adjustments. Low-income Medicare enrollees who participate in Part D face lower out-of-pocket costs under the Part D low-income subsidy provisions. As a result, subsidized beneficiaries may have higher drug expenses than their non-subsidized counterparts and plans may face higher expected reimbursements from low-income subsidized enrollees. CMS implements a set of low-income subsidy adjustors (LIS) to minimize the disincentive for insurance plans to enroll low-income beneficiaries. Low-income adjustors are applied multiplicatively to the standard plan reimbursement rate. In 2006, the low-income subsidy adjustment is about 7 percent for full Medicare-Medicaid eligibles, 9 percent for other Medicaid and other qualifying people with income below 135 percent of the federal poverty level, and 5 percent for beneficiaries whose income is between 135 and 150 percent of the federal poverty level. There is concern that the current CMS LIS adjustments may be too small and may lead to inadequate payment rates to plans that enroll low-income beneficiaries.

To examine differences in drug costs for low-income populations, we conducted two separate analyses. The first analysis addresses the issue of whether the CMS LIS adjustments are adequate, while the second examines the difference in drug spending associated with low-income status after adjusting for diagnoses, age, and sex. Since our data do not have income information, we use an indicator for whether a person was on Medicaid as a proxy for low-income status. For these analyses, we adjusted total spending for each individual to the 2006 level using inflation rates provided by the Office of Actuary. We then reduced the FEP non-institutionalized enrollees' total spending by 19%[2] to reflect the reduced demand for prescription drugs due to less generous Part D benefits compared with the FEP benefit structure. Finally, we pooled non-institutionalized FEP enrollees and non-institutionalized Medicaid beneficiaries and calculated the plan share of spending using the Part D formula. All models are run on plan-covered spending rather than total spending.

The first analysis estimates the CMS model without modification and compares the predicted plan share of spending with the actual plan share of spending for Medicaid enrollees. The predictive ratio (predicted plan spending divided by actual plan spending) is 0.97 for the Medicaid population. This suggests that the CMS model with no ex-post adjustment would slightly underpay (by 3 percent) plans for enrolling Medicaid beneficiaries. However, the ex-post low-income subsidy adjustment, which varies from 5 percent to 9 percent depending on the enrollee's income and assets, seems to sufficiently compensate for the underpayment from the risk adjustment model.

The second analysis differentiates the Medicaid population from the non-Medicaid population by adding a Medicaid dummy as an explanatory variable in the CMS model. This allows us to estimate the difference in plan spending associated with being on Medicaid, given diagnosis, age, and gender. The ratio of the estimated coefficient on the Medicaid dummy to the overall average plan share of spending is 12 percent. This suggests that, everything else being equal, a Medicaid beneficiary is 12 percent more expensive for a plan to cover than a comparable person who is not on Medicaid. However, this does not imply that the current CMS adjustment for low-income beneficiaries is insufficient since the current payments are based on the CMS model with *no* Medicaid dummy. Because Medicaid patients cost more overall after diagnosis, sex, and age is accounted for, the omission of a Medicaid dummy in the model means that the coefficients on other model variables (diagnosis, sex, and age) are biased upward, on net. As a result, the non-Medicaid population is slightly over-paid under the CMS model while the Medicaid population is slightly under-paid before the low-income subsidy adjustments are applied.[3]

Summary and Conclusions

[2] The Office of Actuary estimated that FEP enrollees would have spent 19% less if they faced the same benefit structure as provided by Part D.

[3] If payment was based on coefficient estimates from a model that included a Medicaid dummy, then the LIS adjustment should be based on the estimated dummy coefficient, suggesting an LIS adjustment of about 12 percent.

The purpose of the work described in this report was to further explore the appropriateness of the Part D risk adjustment model for particular subgroups of Medicare beneficiaries. In order to do this, the following basic steps were taken. First, we applied a common set of drug prices to the two data sets being used—the BCBS FEP data and a linked Medicaid-Medicare data file. Once the prices were selected and merged onto the data sets, the two data sets were combined and treated as one. Using the combined data set, we tested whether the linear risk adjustment model was the appropriate specification or whether a model allowing interactions would be a better fit. Our statistical tests indicate that there are missing interaction terms from the linear model. From a policy perspective, this might result in under-payment for specific population sub-groups (and over-payment for others). The under-payment is of particular policy concern because plans might undertake strategies to avoid enrolling such beneficiaries, creating a problem with respect to access to the prescription drug benefit. Medicaid beneficiaries could potentially be singled out by insurance plans due to underpayment. However, our analysis of the appropriateness of the Part D reimbursement to insurance plans indicates that ex-post low-income subsidy adjustments sufficiently compensate plans for enrolling Medicaid beneficiaries.

Chapter 2

CONTINUATION OF DRUG RISK ADJUSTMENT

Task 3: Analysis of Incorporating Lagged Drug Use into Risk Adjustment Models

Purpose and Background

In anticipation of the implementation of the new Medicare Part D prescription drug benefit, during 2005 CMS developed a drug risk adjustment model for the payment of prescription drug plans. The purpose of the drug risk adjustment model is to ensure that payments to plans for prescription drugs used by Medicare beneficiaries are equitable, by accounting for known differences in health status of the enrollees served. The risk adjustment methodology developed for payments to Medicare+Choice/Medicare Advantage plans was refined over a number of years, beginning with the use of a model based on inpatient diagnoses only (the PIP-DCG model) and, more recently, incorporating diagnostic data from outpatient and physician claims as well. The MMA required that CMS consider this current risk adjustment methodology—the CMS Hierarchical Condition Category or CMS-HCC—in developing a corollary model for risk adjusting payments under the drug benefit.

In order to adapt the HCC model for drug risk adjustment, CMS modified the specific conditions included in the model and estimated new weights for those conditions. While CMS has released the drug risk adjustment model, internal work continues on refining and testing the model. In particular, within the next one to two years, CMS will have available actual drug claims data from plans and the potential for incorporating elements of these data into the risk adjustment model is being explored by CMS staff.

The purpose of this task was to explore the inclusion of data from actual drug claims (e.g., lagged drug spending or use) in the drug risk adjustment model. With respect to either spending or use, the focus of this task is on incorporating information from drug claims into a *diagnosis-based* risk adjustment model, rather than on developing a model that depends solely on prior drug use or spending to establish payment. First, we provide a brief synopsis of some of the advantages and disadvantages of using information from drug claims in a risk adjustment model. Second, we review some of the literature on this topic. Then, we present empirical work that was previously conducted for ASPE that incorporated past drug spending into different risk adjustment models, and we update this work using more current data and based on the more recent CMS risk adjustment model. The analysis is expanded to explore incorporation of a limited amount of information on drug

utilization rather than spending. Finally, we provide some general recommendations based on the empirical findings with a particular emphasis on the potential impacts on incentives facing plans.

A Brief Review of Literature on Drug Risk Adjustment

The purpose of this literature review was to learn about any previous work on risk adjustment models aimed at paying for prescription drugs. While there are many similarities in the underlying methods behind predicting overall health care spending and drug spending, there are a number of differences that made it critical for CMS to invest in development of a model specific to drugs. For example, work conducted in 2001 showed that person-level drug spending is much more stable from year to year than is total health care spending, and drug spending and total Medicare spending often move in opposite directions as severity of illness increases (Hogan, 2001).

However, in contrast to the vast amount of knowledge that has been accumulated in developing the HCC and other risk adjustment methods to predict overall health care spending, there has been substantially less work conducted that focuses on predicting drug spending alone. A number of studies involve the use of pharmacy data in a risk adjustment model; however, the majority of these still focus on predicting total health care spending rather than drug spending. We begin by reviewing these models as they shed some light on using pharmacy claims for risk adjustment even though they are not directly applicable to our underlying purpose.

Advantages and Disadvantages of Using Drug Claims in Risk Adjustment

From the literature reviewed, we found several justifications for using pharmacy claims in addition to or instead of diagnostic information to risk adjust *total* spending. The first and perhaps most often-cited reason is that drug claims, as compared to outpatient or inpatient claims, are easier to obtain and more timely because of electronic processing. This first advantage of using drug claims applies primarily if one is considering the substitution of drug claims for inpatient or outpatient claims, rather than using them in a complementary fashion as is the goal here. If both types of claims are being used, then the speed of processing for one set of claims does not by itself increase turnaround since the completion of the model must still be delayed until medical claims are processed.

A second rationale for the use of drug claims is that, because drug claims do not depend on physician coding practices, they may tend to be more reliable and less subject to potential error or gaming behavior.[4] Full reliance on a diagnosis-based model could potentially disadvantage plans with less control over the amount and quality of diagnosis data reported for their enrollees. For example, Medicare Advantage plans have the ability to require physicians to adhere to specific coding practices, while stand-alone prescription drug plans (PDPs) are unable to affect physician

[4] The incentives for prescribing of more drugs that may be the result of relying on lagged drug use are discussed below.

coding since the drug plan is independent of other health care services.[5] Thus, if there are concerns about the ability of certain plans or plan types to obtain adequate or complete diagnosis data, then model developers may decide to substitute information on drug use for diagnostic data or incorporate prior drug use within a diagnosis-based risk adjustment model.

Finally, information on drug use may be correlated with the presence of specific chronic conditions, so that information on prior drug use may substitute for missing diagnostic data or improve the quality of information related to certain diagnoses. With respect to this justification for including drug claims, there is still a considerable amount of research that would need to be done prior to adopting this approach.

There are also a number of disadvantages to using pharmacy data. Several articles we reviewed note that a risk adjustment system based on pharmacy claims will have to be updated more frequently than one based on diagnostic data. This is because of the frequency with which new drugs enter the market, are approved for new uses, or are discontinued. In contrast, diagnoses change much less often. The necessity of more frequent updating would have the most serious implications for a risk adjustment system based solely on pharmacy claims, but would also be relevant for a model where drug claims are used in addition to other service claims.

Thus far, the discussion has focused on drug use information rather than drug spending. However, perhaps the most important limitation to using information about prior drug spending (and to a lesser extent, prior drug use) is specific to a drug risk adjustment model (rather than one for overall health care spending) and has to do with the incentives that may result. Incorporating prior spending (or possibly prior use) may provide perverse incentives for plans--penalizing plans that are efficient while rewarding plans that are not. If we think of efficiency as having a price and a quantity component, then the payment system should ideally result in plans having incentives to (i) purchase drugs at the lowest possible price and (ii) purchase that quantity of drugs that will produce the greatest health in its enrollees. Purchasing the right quantity of drugs has many dimensions—which individuals get drugs, the quantity for those individuals who are prescribed any drugs, the appropriate mix of brand names and generics, the appropriate mix by therapeutic class, and so on.[6] In general, including lagged drug spending could lead to inefficiencies through higher prices *and* larger quantities, while incorporating lagged drug utilization should affect only the quantity component. The former result comes about because reimbursement is directly tied to the level of past spending so that higher-priced drugs and larger numbers of drugs lead to higher reimbursement. In contrast, reimbursement that is related to prior use may provide incentives for

[5] There is some sentiment that PDPs (providing drugs only) may be disadvantaged relative to M+C plans because PDPs are unable to influence coding behavior of physicians, on which reimbursement for drugs will depend in a fully diagnosis-based model. To the extent that there are gains in quality from an integrated system like the M+C plans, however, policy makers may not want to adapt the risk adjustment mechanism to compensate for this difference.

[6] It is worth noting that there are different incentives for over- or under-prescribing, and the pricing of drugs according to strength, form, or dosage makes any general discussion difficult. A complete discussion of the issues surrounding "appropriate" prescribing is beyond the scope of this paper.

larger numbers of drugs, but reimbursement should not be affected by the prices paid by individual plans.

An additional concern about including data about either prior drug use or spending has to do with the extent of geographic or plan-provider variation in prescribing patterns and hence drug utilization. This variation could lead to inequities in payments across plans or parts of the country, with plans or physicians that prescribe more drugs receiving higher payments. Under this sort of arrangement, plans that contract with physicians who prescribe fewer drugs for a given health status, or beneficiaries who live in parts of the country with similarly conservative prescribing styles may be penalized unfairly.[7] While diagnosis-based risk adjustment may provide incentives for over-recording of diagnoses or may differentially reward variation in recording patterns, this is likely to have less of an adverse impact on either beneficiary health or overall health care costs.

Predicting Health Care Spending

Findings from the literature based on using pharmacy claims to predict total spending; while not directly relevant to a drug risk adjustment model per se, shed some light on the relationship between drug claims and chronic conditions. Gilmer, Kronick, Fishman and Ganiats (2001) explored the use of drug data to better predict health care expenditures for a Medicaid beneficiary population. Using pharmacy claims–with drugs grouped together based on therapeutic class--both as a substitute and in addition to diagnostic data, they conclude that a combination of pharmacy and diagnostic data is superior to either type alone in predicting spending. However, they find variation across sub-populations (Medicaid disabled vs. TANF) in the ability of pharmacy vs. diagnosis data to predict costs. Examining three specific conditions—diabetes, mental illness, and cardiovascular disease—they find substantial differences in the strength of diagnosis vs. pharmacy data. For example, using diagnostic data better predicts diabetes whereas using drug claims provides better information about the existence of mental illness.[8] These findings suggest that pharmacy data can indeed be used effectively to supplement diagnostic information with respect to some conditions, though the authors note that the effect on incentives for plans from using a broad range of data on prior drug use is not clear.

[7] The MMA requires the Secretary to examine the need for adjusting payments based on evidence of geographic variation in prices and spending. Geographic adjustments could relate to two different factors: prices and spending. Specifically, the MMA requires the Secretary to develop a way to adjust plan payments for variations in drug prices across regions, starting in 2006, unless these price variations are determined to be *de minimis*. The Secretary is also charged with reporting to Congress on variations in per capita spending among PDP regions for covered Part D drugs. For that report, due in 2009, the Secretary must distinguish spending variation that is attributable to price variations versus that due to differences in utilization. The report will also include recommendations on possible changes to the geographic risk adjustment factor to take utilization into account.

[8] To illustrate, for all disabled adults identified with diabetes by either a diagnostic code or a prescription, 10% did not have a diagnosis of diabetes in a given year and 22% did not have a record of filling a drug for diabetes. Of those without a prescription, 87% had a diagnosis of Type 2 diabetes which can be managed effectively by diet and exercise.

Similarly, Lamers (1999) used pharmacy data to ascertain the presence of chronic conditions in a risk adjustment framework. Compared to an initial model that included only demographic data and no diagnostic information, the use of pharmacy data not surprisingly substantially increased explanatory power. The author notes that the use of lagged prescribed drugs in a capitated model may provide perverse incentives to plans (e.g., to prescribe more drugs), and suggests employing a small number of condition categories to mitigate this behavior. Fishman et al. (2003) developed the RxRisk model, a risk assessment instrument that uses automated ambulatory pharmacy data to identify chronic conditions and predict future health care costs, and compared its forecasting power with a demographic-only model, the Ambulatory Clinical Groups (ACG), and the CMS-HCC model. HCCs were found to produce the most accurate forecasts of total costs relative to either RxRisk or ACGs. However, RxRisk was found to perform similarly to ACGs and, of interest, all three models had similar explanatory for the middle 60 percent of the cost distribution. It should be noted that they separately tested the use of diagnostic vs. pharmacy data, but did not use the two types of data in combination. Sales et al. (2003) applied the RxRisk model to a Veterans Health Administration data and found that, for prospective cost models, the explanatory power of the model was comparable to that of the ACG or HCC models. Powers et al. (2005) used Pharmacy Health Dimensions (PHD), an alternative pharmacy-based risk index, to predict total health care costs, including pharmacy costs. Like the previous work, they found that pharmacy data can reasonably predict health care spending.

Predicting Drug Spending

Wrobel et al. (2003/2004) used the Medicare Current Beneficiary Survey (MCBS) and diagnostic information from linked Medicare claims with the CMS-HCC model to predict prescription drug expenditures. Limiting the independent variables to demographic characteristics, the model explained only 5 percent of the variation in drug expenditures. Adding the diagnostic groups used in the HCC model increased the explained variance to 10 to 24 percent. Of particular interest, adding lagged drug use increased the R-squared to 55 percent. One conclusion drawn by the authors is that it is persistent, chronic conditions that drive drug spending. They also note that because lagged expenditures add significant explanatory power when diagnoses are already included in the model, there is a strong incentive for plans to risk select even with risk-adjusted payments. This should signal added caution in incorporating these measures into the payment system.

Zhao et al. (2005) developed models to predict drug costs as well as overall health care costs. Similar to Gilmer et al., they found that total health care costs were best predicted using both diagnostic and drug data, though they conclude that diagnostic data alone outperforms drug data alone. Like Wrobel et al., they show that models predicting drug spending had higher R^2 values than those predicting health care spending, and that drug claims were very predictive of future prescription drug costs.

It should be noted that in all of these studies the models are assessed primarily based on explanatory power and are unable to directly address how behavior might be affected by inclusion or exclusion of a given set of variables. Relatively little attention is paid to the impact of the different models on

incentives for plan risk selection in the context of a benefit such as Part D. While their research indicates the usefulness of prior drug use in model development, additional empirical work is needed to better understand how drug data can be used to improve the model's ability to capture beneficiary health status without the creation of unwanted incentives.

Analysis of Risk Adjustment Model Incorporating Drug Spending or Use

In this section of the report, we provide empirical analysis and discussion of the impact of incorporating, first, prior drug spending and, then, prior drug use into the existing CMS-HCC drug risk adjustment model. It is important in so doing to think about the purpose of such a potential change to the model. An accurate risk adjustment process is critical from the perspective of the Medicare program--in terms of fairly paying plans for the services delivered, allocating funds equitably between private plan beneficiaries and beneficiaries in traditional Medicare, and still maintaining appropriate incentives for plans. The risk-adjusted payment must be adequate to induce continued participation on the part of plans and, at the same time, it must accurately reflect actual health status and expenditures so that plans compete with respect to benefits and services rather than through gaming the system (e.g., attracting low-cost enrollees). Thus, the decision to include additional variables in the model, beyond diagnoses and demographic data, should be based on the assumption that the additions will further these objectives. On the one hand, it should be considered whether information about past drug use might provide important information about health status that is somehow missing from existing claims or, on the other hand, whether inclusion of information about past spending or use will provide inappropriate incentives similar to cost-based reimbursement. The empirical analyses discussed below should then be assessed within this framework.

Prior Work Incorporating Drug Spending

In October 2000, Direct Research completed an initial analysis of drug risk adjustment for ASPE. As part of that work, regressions were run predicting drug spending based on prior year diagnoses and spending. The data used were pooled 1992 to 1997 Medicare Current Beneficiary Survey Cost and Use files, and the diagnosis categories were based on the Disability Payment System (DPS). The dependent variable was total drug spending from all sources (beneficiary out-of-pocket plus insurer).

That analysis showed two relevant facts:

- The regression coefficient on lagged drug spending was 0.75. That is, every additional dollar of drug spending in the base year predicted an additional $0.75 of drug spending in the current year.
- If lagged spending is included in the regression, the diagnosis data hardly matter. The explanatory power (R-squared) of lagged drug spending alone was 0.52; the explanatory power of lagged drug spending plus diagnoses was 0.53.

The obvious explanation for these findings is that an individual's drug spending is strongly serially correlated. Most medications are for chronic illnesses, and most beneficiaries who take a drug will continue taking it for an extended period or even for life. Thus, prior year drug spending is a strong predictor of current-year drug spending.

Update of Prior Analysis of Drug Spending

The prior analysis was updated in the following ways:

- Instead of using 1992-1997 data, the data were pooled MCBS 1997-2001 Cost and Use files (the most recent available under this project).
- The risk adjustment model used was the CMS-HCC model that was developed for drug plan payment under the new Medicare Part D benefit.
- The spending data used were inflated to a mean of $2500, and the MMA benefit structure was modeled to yield two dependent variables: (i) total drug spending (from all sources), and (ii) plan-covered drug spending net of reinsurance (the amount on which the plan should base its premium bid).

Compared to the earlier work reported on above, the results of the analysis did not change significantly (see Table 1). When lagged spending is added to the diagnosis-based risk adjustment model, the coefficient on the lagged drug spending variable is still about 0.75 (Table 1, right-hand column). As well, diagnoses do little to add to the explanatory power of lagged drug spending. The R-squared of the regressions increases by one to two percentage points, from 0.59 to 0.60 for plan-covered spending net of reinsurance, or from 0.49 to 0.51 for total drug spending.

Table 1: Using Lagged Drug Spending As A Risk Adjuster

	Diagnoses Alone		Lagged Spending Alone		Diagnoses+Lagged Spending	
Dependent Variable	R-squared	Coefficient on lagged spending	R-squared	Coefficient on lagged spending	R-squared	Coefficient on lagged spending
Plan spending net of reinsurance	0.25	n/a	0.59	0.81	0.60	0.74
Total drug spending	0.21	n/a	0.49	0.83	0.51	0.75

Source: Analysis of MCBS 1997-2001 Cost and Use files, pooled. Other regressors in the equation include age, sex and drug HCC diagnosis categories.

Incorporating Drug Use

The analysis reported above indicates that a simple drug risk adjustment model using prior-year spending as the risk adjuster would have several significant drawbacks; mainly, such a system

would substantially weaken incentives for efficiency, as it would reimburse plans roughly 75 cents out of every additional dollar spent, and penalize plans 75 cents out of every additional dollar saved.

The question addressed here is whether a system based on other, more refined measures of prior-year drug use could avoid the problems of the simple, total-spending prior use model. This question is addressed by constructing some plausible prior use models based on the utilization of selected types of drugs in the base year.

Prior use models constitute a fundamental change in risk adjustment strategy, relative to the diagnosis-based models currently used for risk adjustment of acute-care spending. To understand this, consider what types of risk adjustment models for acute-care spending would be analogous to the prior use models being considered for drug spending. For example, the presence of service use by Berenson-Eggers Type of Service (BETOS) category, or the presence of hospital discharge by major diagnostic category, could have been used to predict total acute-care spending. In fact, the earliest CMS risk adjustment method (the diagnostic cost group model) was a prior use model (relying on prior use of selected categories of hospital discharges), and was abandoned as soon as possible for a site-neutral diagnosis-based model that did not rely on prior use of hospital care to generate predicted spending.

In general, the incentives from prior use models will differ somewhat from the incentives from prior spending models. As discussed earlier, under a prior use model, plans have full incentives to pay the lowest possible prices for drugs since prior use models ignore the prices paid and only focus on the units of drugs purchased. Prior spending models, by contrast, reduce plans' incentives to seek the lowest possible price on drugs, because part of the price reduction would be taken back in reduced government risk-adjusted payments.

The main issue to be tested here is whether prior use models differ substantially from prior spending models. If enough separate drug categories are included, or if the models count the number of prescriptions by category, will the prior use models give predicted values that are essentially the same as prior spending models? If so, then prior use models inherit all the incentive drawbacks of prior spending models. If not, however–if the prior use models generate payment rates that are significantly different from the prior spending models–then prior use models may offer some benefits that warrant further investigation as potential risk adjustment models for Medicare Part D.[9]

Data and Methods. The analysis relied on the MCBS 1997 to 2001 Cost and Use files. Consecutive two-year panels of data (persons in 1997 and 1998, persons in 1998 and 1999, and so on) were assembled. In the base year of each two-year panel, claims were summarized and the drug HCC risk adjustment model categories were calculated. In the second year of each two-year panel, drug spending was summarized--both total spending and plan-covered spending--based on the spending

[9] The prior use models presented are fairly simple based on the scope of this task. As discussed elsewhere in the paper, CMS' current thinking about a prior use model would incorporate drug use related to specific conditions only. Developing and testing such a model is beyond the scope of this project.

observed on the file (i.e., with no actuarial adjustments to account for existing coinsurance rates). Persons with incomplete claims data, no drug data, or with an MCBS person ID that could not be tracked from year to year were eliminated. This includes the institutionalized (no drug data), those in MA plans or hospice in the base year (no claims), and MCBS ghosts (ID changes across years). All of these two-year panels were combined to form one large dataset, after setting mean drug spending to $2500 in each year. Across all years pooled, there were 21,758 observations. Here, we describe the construction of the drug type categories using MCBS data.

Developing a working set of drug categories is not straightforward. MCBS has drug names but not National Drug Codes (NDCs) on the file, making it possible but difficult to match the MCBS data to external files with drug categorizations. MCBS itself has a limited drug categorization variable dividing drugs into roughly three dozen functional classes. Earlier work for ASPE demonstrated that the MCBS drug categorization differed substantially from the FDA Orange Book drug classification, for example, in the classification of drugs as diuretics (MCBS) versus antihypertensive medications (FDA Orange Book). Thus, for this analysis, information was restricted to drug categories that could be constructed directly from the MCBS. In practice, that meant either letting each drug name stand alone, or using the pre-defined MCBS drug categorization.

The approach shown here is to investigate some prior use models by running variations of the basic model and comparing them to a model based on prior year drug spending. The results show how the number of drug categories affects the model's explanatory power, and how close the prior use models come to the prior spending model.

For the models using individual drugs, the most frequently used drugs are entered into the model first. Thus, the model with 10 drug categories has the 10 most frequently mentioned drug names in the MCBS. As the number of categories in the model is expanded, drugs are added in decreasing order of frequency of mention within the pooled MCBS files.

Results: Table 2 shows the results of the regressions predicting current-year total drug spending from prior-year drug utilization by category. The drug categories are indicated by rows in the table—each row corresponds to a number of the most-commonly reported drugs. Three different types of drug counts are used (shown in each of the three columns in the table): (i) a 0-1 indicator flagging the presence of any prescription in the drug category; (ii) a count of the actual number of prescriptions in the drug category; and (iii) a 0-1 indicator flagging the presence of two or more prescriptions in that drug category.

The first set of rows shows what happens as the presence of the N most frequently prescribed drugs is entered into the model, where N ranges from 10 to 1000. The clearest finding is that it makes little difference whether one flags any prescription, counts the total number of prescriptions, or flags only persons with multiple prescriptions within a category. This can be seen by looking at any one row of Table 2; one can see that the explanatory power of the model and the correlation of that model's predictions with the predictions from the prior spending model appear to be roughly the same no matter which variation is used. For example, including the top 10 drugs, the R-squared

varies only from 0.12 to 0.13 depending on the specific count variable used, and the correlation with the prior spending model varies only between 0.39 and 0.43.

The second conclusion is that models with a moderate number of drug categories will have lower explanatory power than the prior spending model, and will generate predicted values that are only modestly correlated with predicted values from the prior spending model. So, for example, the model using the MCBS 36 functional drug categories has an R-squared of between 0.30 and 0.36 depending on the count variable used (versus 0.46 for the prior spending model). The model using individual drugs approaches the explanatory power of the prior spending model only when 500 to 1000 drugs are allowed to enter separately into the model.

Table 2: Explanatory Power of Simple Prior use Drug Risk Adjustment Models

	Any Prescription		Count N of Prescriptions		2 or More Prescriptions	
Prior Use Model	**R-squared**	**Corr. With Prior Spend Model**	**R-squared**	**Corr. With Prior Spend Model**	**R-squared**	**Corr. With Prior Spend Model**
Top N Drugs						
10	0.12	0.39	0.13	0.43	0.13	0.41
25	0.18	0.49	0.19	0.53	0.19	0.51
50	0.25	0.56	0.25	0.61	0.26	0.60
100	0.29	0.61	0.30	0.67	0.31	0.65
250	0.35	0.66	0.36	0.73	0.37	0.74
500	0.40	0.70	0.42	0.78	0.43	0.75
1000	0.46	0.74	0.47	0.80	0.49	0.78
MCBS 36 Drug Categories	0.30	0.62	0.36	0.76	0.34	0.67
Any MCBS Drug	0.07	0.31	0.33	0.72	0.09	0.34
Prior Spending Model	0.46	1.00				

Source: Analysis of MCBS Cost and Use Files, 1997-2001

A third potentially interesting finding is that simply counting the number of prescriptions appears to do about as well as separately categorizing the top 100 drugs. Flagging the presence of "Any MCBS Drug" and counting the number of prescriptions (middle set of columns) yields an R-squared of 0.33, only slightly worse than the R-squared from separately flagging the top 200 drugs.

If the models are arrayed by decile of prior-year spending (Table 3), the principal advantage of the prior spending model becomes clear. The prior spending model does an excellent job of predicting spending for the costliest beneficiaries, but predicts too high a level of spending for the lowest-cost beneficiaries. The prior use models, by contrast, grossly under-predict for the costliest patients, and over predict for low-cost beneficiaries unless a very large number of drug categories is included in the regression.

Table 3: Actual and Predicted Spending by Decile of Prior-Year Spending

				Current Year Dollars Predicted By:				
Decile	**N in Sample**	**Actual Prior Year $**	**Actual Current Year $**	**Prior $ Model**	**Top 10 Drugs**	**Top 50 Drugs**	**Top 250 Drugs**	**Top 1000 Drugs**
Total	21,759	$ 2,500	$ 2,500	$ 2,500	$ 2,500	$ 2,500	$ 2,500	$ 2,500
1	2,185	$ 1	$ 195	$ 831	$ 1,613	$ 980	$ 539	$ 391
2	2,229	$ 154	$ 466	$ 941	$ 1,924	$ 1,349	$ 967	$ 825
3	2,168	$ 500	$ 918	$ 1,162	$ 2,089	$ 1,629	$ 1,352	$ 1,252
4	2,191	$ 908	$ 1,361	$ 1,449	$ 2,280	$ 1,979	$ 1,808	$ 1,704
5	2,157	$ 1,364	$ 1,846	$ 1,722	$ 2,396	$ 2,234	$ 2,143	$ 2,063
6	2,153	$ 1,899	$ 2,259	$ 2,087	$ 2,556	$ 2,507	$ 2,496	$ 2,415
7	2,170	$ 2,559	$ 2,773	$ 2,531	$ 2,727	$ 2,852	$ 2,936	$ 2,908
8	2,144	$ 3,425	$ 3,422	$ 3,108	$ 2,899	$ 3,213	$ 3,389	$ 3,388
9	2,157	$ 4,806	$ 4,487	$ 4,023	$ 3,070	$ 3,696	$ 4,004	$ 4,037
10	2,205	$ 9,380	$ 7,271	$ 7,143	$ 3,446	$ 4,561	$ 5,373	$ 6,049

Source: Analysis of MCBS Cost and Use Files, 1997-2001

This second conclusion is reassuring. Based on earlier work, we do not want the prior use model to come too close to a model based on prior spending. The prior spending model has significant incentive and policy downsides. With these results we can be reasonably sure that the prior use models do not closely approximate the undesirable prior spending model unless a large number of drug categories are used.

Summary and Conclusions

The results from the empirical analyses have important implications for a policy of using lagged drug spending as a risk adjuster for Medicare drug plan payment. Most importantly, use of lagged spending as a risk adjuster substantially weakens incentives for price competition and efficiency. If the regressions presented above were used for risk adjustment, then the risk adjuster alone would compensate plans for 75 percent of the variation in their costs, no matter what the source of that variation. That is, a plan with costs 20 percent above the average in one year would expect to recoup 15 percentage points of that in the next year. Similarly, a plan with costs 20 percent below average would expect to lose 15 percentage points of that in payment the following year. This means that an extremely efficient plan would see three-quarters of those efficiency gains taken back

by the taxpayer, while an extremely inefficient plan would see three-quarters of its higher costs subsidized by the taxpayer. This clearly weakens any incentives for efficiency or for application of stringent coverage or payment rules that would reduce total plan outlays.

In addition, use of lagged spending as a risk adjuster negates the use of a diagnosis-based risk adjuster. Prior-year diagnosis information adds little to the explanatory power of the risk adjustment model, once lagged spending is included. So, if prior spending were to be used for drug risk adjustment, the method of payment for Medicare Part D would be fundamentally different from that used under Medicare Part C.

Our results indicate that the inclusion of prior *use* rather than prior *spending* produces models that are significantly different and more appealing from a policy perspective. Models with a modest number of drug categories have lower explanatory power than the prior spending model, and generate predicted values that are only modestly well correlated with the predictions from the prior spending model. From the perspective of plan incentives and efficiency, these conclusions are positives in that the prior use model should not be a close proxy for a prior spending model.

It does not seem to matter much whether the presence of drugs was included based on a single prescription, multiple prescriptions, or a count of the number of prescriptions within the drug category. Thus, developers of a drug risk adjustment model incorporating some elements of prior use would have significant latitude to choose the method that gave the best combination of incentives and robustness toward variations in data reporting or variations in practice patterns. For example, CMS might avoid models using a count of prescriptions due to the creation of incentives to prescribe more, with the understanding that the use of the count of prescriptions would add only modestly to the overall explanatory power of the regression in any case.

Of those measures examined here, the "any prescription" indicator potentially comes closest to improving missing or unmeasured diagnostic information without affecting incentives adversely. However, before any additions are made to the diagnosis-based risk adjustment model, additional empirical work is required. If the purpose is to augment diagnostic information, then clinical and empirical work must be used, first, to establish the connection between specific health conditions and particular drugs and, secondly, to investigate the extent to which the drug data truly increases the measured information on diagnoses.[10] There are several different approaches to such work.

One option would be as follows: such an empirical exercise might select a condition X where a substantial proportion of persons use a particular drug Y. Then, one could look at the number of users of the drug Y who did *not* have a diagnosis for condition X in the base year. To the extent that drug Y is clinically important in treating condition X, then this measures the level of missing diagnostic information for condition X. This analysis is similar to that performed by Gilmer et al.; they examined the extent to which the presence of diabetes, mental illness, and cardiovascular disease were identified by a prior diagnosis, prior drug use, or both. Again, to illustrate: if diabetes is

[10] CMS is currently working with a consultant pharmacist on some sort of mapping of drugs to health conditions.

the selected condition, one would use base year claims to look for either a diagnosis of diabetes, use of a diabetes-related drug, or both. The extent to which the prior drug use identifies persons not flagged by diagnostic codes gives some indication of the utility of using prior use in identifying persons with diabetes. Of course, this process assumes that a strong link has been established clinically between the health condition and the prescription drug.

If one concludes that both diagnostic and drug use data have potential limitations, then it may make sense to use a hybrid risk adjustment model. Whether a hybrid model can accomplish the twin goals of improving the risk adjustment model through adding important health status information and maximizing incentives for efficient plan behavior depends, at least in part, on the relative emphasis placed on diagnoses and prior use. A conceptual framework might be similar to Newhouse's "partial capitation" payment method, under which plans are paid based on a blend of capitation and fee-for-service payment (Newhouse, 1994). Policy makers might be given the option to choose how strongly they wish to rely on prior drug use as a payment adjuster. The simplest way to do that is to calculate the risk-adjusted rate as a blend of the diagnosis-based rate and the rate based on diagnoses and prior use (e.g., half of the diagnosis-based rate plus half of the diagnosis-plus-prior use rate). Under this approach, the payment weight given to prior use is not based on the (arbitrary) output of the regression model, but would be chosen as a policy parameter to balance, as well as possible, issues of incentives and payment fairness.

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Chapter 3

CONTINUATION OF DRUG RISK ADJUSTMENT

Task 4: Analysis of Differences in Drug Use and Pricing

The Medicare Modernization Act required that the Department conduct a study of geographic variation in drug utilization and spending to determine whether some further adjustment to Medicare prescription drug plan payments may be necessary beyond the risk adjusters. That report, which must be sent to Congress by 2009, should address whether the underlying causes of geographic variation, if such variation is substantial, include factors outside the control of beneficiaries and those doctors who prescribe medications for them. Thus, for example, there might be health status factors beyond those measured by the risk adjusters or structural differences in the health system that lead to different levels of drug use in one part of the country versus another. By contrast, if geographic differences in prescription drug use are related to differences in insurance coverage, choices made by beneficiaries of whether to purchase prescribed medications, or the varying propensity of doctors to prescribe medications for a particular health condition, there may be no reason to make adjustments.

This report offers a preliminary look at questions of geographic variation using 2002 claims data for federal retirees, age 65 and older, who are on Medicare but get their drug coverage through the Blue Cross/Blue Shield Federal Employees' Plan (FEP). In the first section of this report, we look at geographic variation among the 34 Prescription Drug Plan (PDP) regions established for Medicare Part D. In the second section of this report, we look at variation within PDP regions, between metropolitan and non-metropolitan areas.

Geographic Variation in Drug utilization and spending Among Regions

In this section, we discuss the variation among regions in drug spending, utilization, and costs. In previous work for ASPE, we looked at actual spending in FEP, as well as risk-adjusted projected spending under Part D. While risk adjustment tempers some of the differences, both measures show substantial variation. In that analysis, we presented results by state, because the regions for standalone prescription drug plans had not been announced when we began our analysis. We present the results here by PDP region. There were 34 regions, excluding the territories, established for offering standalone drug plans.

Unadjusted FEP plan spending (2002) includes the amounts paid by the plan but excludes enrollee cost sharing, as provided on the original FEP file. By region, FEP spending ranged from $1,528 per person in Alaska (15% below the national average) to $2,011 per person in Georgia (12% above the national average) in 2002.

Risk-adjusted projected plan spending includes only the estimated payments a plan would make under the Part D benefit, taking into account the impact of the deductible, initial coverage period, coverage gap, catastrophic coverage, and overhead expenses. This measure is inflated to reflect projected 2006 prices and adjusted to account for the case mix of the enrollees in each state, as measured by the CMS risk-adjustment model (January 2005 version). The risk adjuster reduces geographic variation, but a substantial amount of variation remains. After risk adjustment, projected plan spending ranges by region from $1,434 in New York (11% below the national average) to $1,711 in Oklahoma (6% above the national average). In general, high-cost and low-cost PDP regions tend to remain high-cost or low-cost after risk adjustment. There are also regional patterns to this variation, both before and after risk adjustment. States in the southeast and mid-Atlantic tend to have spending above the national median, while states in the northeast and the west tend to have spending below the national median. Details of spending by region are available in the Appendix.

The variation in these two measures is summarized in Figure 1 and Figure 2. These box plots represent the range of variation in each measure: a measure with a wider box has more variation. We present values in these plots as ratios to the average of each measure. In each plot, the center line represents the median of the distribution of all regions. The box surrounding the median represents the 50 percent of regions that fall within the interquartile range, while the lines extending to the left and right of the box represent the lowest and highest quartiles of regions. [11]

For example, Exhibit 1 shows that the lowest-spending region (the dot on the left) had spending about 15 percent lower than the national average, while the highest spending region (the dot on the right) had spending 12 percent above the national average. The 25 percent of regions with the lowest spending fall within the range from 15 percent below the national average to 7 percent below the national average (the line extending to the left of the box). The second quartile of regions have spending from 7 percent below the national average to 2 percent above the national average (the left-hand side of the box). The third quartile of regions have spending ranging from 2 percent above the average to 7 percent above the average (the right-hand side of the box), with the highest-spending quartile ranging from 7 percent above the average to 12 percent above the average (the line extending to the right of the box).

[11] The vertical dotted lines that are unconnected to the box, known as "fences," represent cut-offs for outlier values. The cutoff for outliers is the point that is 1.5 times the interquartile range beyond the 25th percentile and the 75th percentile. For example, in Figure 2, the 25th percentile is at .97, and the 75th percentile is at 1.03. The difference is .06, the interquartile range. Therefore, the lower fence is at (.97-(1.5*.06)), or .88, and the upper fence is at (1.03+(1.5*.06), or 1.12. In subsequent plots, when there are outliers, they are shown as dots or asterisks unconnected to the boxplot. When these fences are outside the range of any actual values, they are left out of the charts.

We use this same method of presentation, on the same scale, for box plots throughout this paper. Normalizing the values as a ratio to the average of each measure allows us to compare the magnitude of variation in different measures. Thus, by comparing Figure 1 and Figure 2, it is clear that there is less regional variation in risk-adjusted plan spending than in actual plan spending.

Figure 1. Variation in Actual FEP Plan Spending, 2002

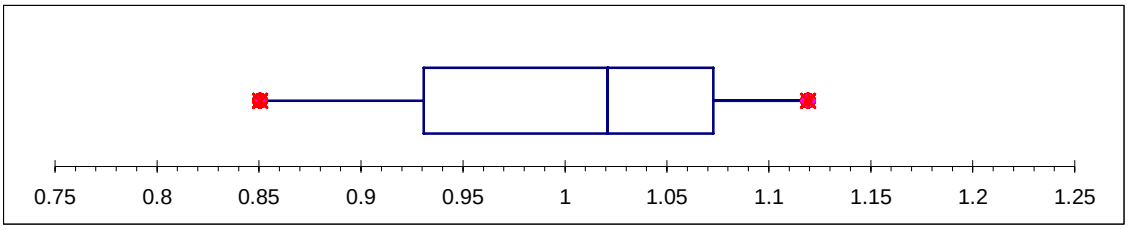
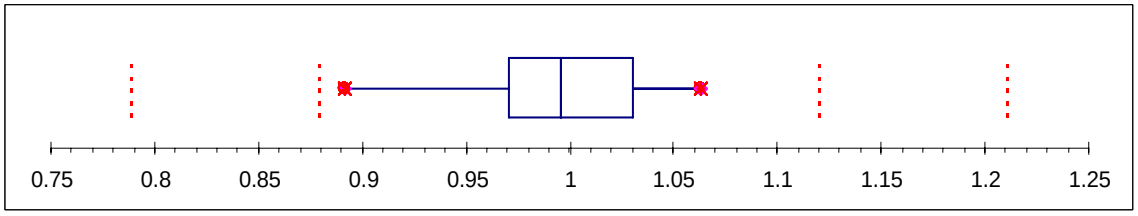


Figure 2. Variation in Risk-Adjusted Projected Plan Spending, 2006



These measures of the regional variation in overall spending provide the background for this report's in-depth examination of the factors that contribute to spending.[12] In the following sections we explore in more detail some of the components of overall spending. Specifically, we have broken these components into two major categories: utilization and costs. For both utilization and cost, we will examine the variation in several factors.

Factors Contributing to Variation: Utilization

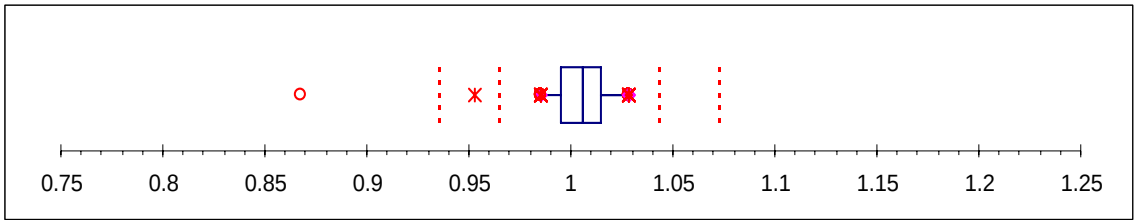
The first component that we will examine for its contributions to spending variation is utilization. There are two major factors of utilization that can be isolated. First, we will examine what proportion of each region's population uses any prescription drugs; then we will consider the quantity of drugs used by those individuals who did have drug claims. In addition, we will look at use in particular classes of drugs and how utilization for certain classes may be driving differences in utilization overall.

[12] In the sections that follow, we use data that have not been risk-adjusted. Rather, we describe elements of utilization and prices as observed in several different data sets to gain some insight into the overall variation. As with overall spending, some of the variation in these individual factors may be explained by the health of the population.

Proportion of Individuals with Non-Zero Drug Spending

One component of utilization is the proportion of people who fill at least one prescription during the year. We find very little geographic variation in this measure. Typically, just under a tenth (9 percent) of the retiree population of a region uses no prescription drugs. The MCBS shows slightly fewer non-users of drugs, approximately 7.8 percent nationwide.

Figure 3. Variation in Proportion of Individuals with Non-Zero Drug Spending, by Region, 2002



As shown in Figure 3, all but one region were five percent or less away from this national average, and all but two regions were three percent or less away from the national average. (Details are available in the appendix.) The extreme outlier is Alaska: only 79 percent of Alaskan enrollees had claims for prescription drugs. This is consistent with Alaska's low overall spending per person, which is also the lowest in the nation. The other outlier is Hawaii, where 87 percent of FEP retirees used prescription drugs. Correlation between this measure and unadjusted overall spending is .65.

We compared health status, demographics, and certain supply factors for the third of regions with the lowest proportion of users to the third of regions with the highest proportion of users (Figure 4). Regions with a higher proportion of users had a significantly higher proportion of Medicare enrollees under age 65, and a higher proportion of individuals with diabetes, hypertension, or physical or mental limitations, but a lower proportion of heavy drinkers.

Figure 4. Possible Explanatory Factors for Variation in Proportion of Retirees with At Least One Prescription

	Average of bottom third	Average of top third	t stat: top third vs. bottom third	t stat: multiple regression
% with at least one prescription	89%	93%		
Average risk score	0.97	1.00	1.99	1.69
% of people living in a metropolitan area	75%	67%	-1.27	0.19
% High school graduate or higher	87%	84%	-1.81	-0.78
HMO Penetration Rate	23%	16%	-2.00	1.75
Non-Federal Physicians per 100,000 population	265	227	-1.98	**-2.55***
Estimated # Licensed Pharmacists per 1,000 people	10.68	8.12	-1.47	1.01
% Medicare Enrollees (A &/or B) Under Age 65	14%	17%	**3.59****	1.27
% Medicare Enrollees (A &/or B) Over Age 85	11%	10%	-0.99	**2.21***
% heavy drinkers	6%	5%	**-3.65****	**-2.11***
% with asthma	12%	11%	-0.57	-0.94

% with high cholesterol	33%	33%	0.46	0.74
% with diabetes	7%	8%	**3.58****	-0.32
% limited by physical, mental or emotional problems	17%	20%	**2.76***	1.21
% reporting good or better health status	85%	83%	**-2.86***	1.49
% with hypertension	24%	28%	**4.45****	0.42
% current smokers	22%	24%	1.35	-0.19

* Significant at the 5% level ** Significant at the 1% level
Sources for demographic and health status variation are given in the appendix.

However, in a multiple regression controlling for all of these factors, few remain significant, possibly because of the high correlation between some factors. Two new factors emerge as significant: the number of physicians in a region, and the number of Medicare enrollees over age 85. An increase in the number of physicians appears to decrease the number of people using prescription drugs. This is consistent with our findings in previous work for ASPE that regions with higher overall drug spending have a lower number of physicians per capita. This seems to imply that rather than additional doctors leading to additional prescription drug users, there is a more complex relationship between physician care and pharmaceutical use. It could be the case that additional physicians lead to a healthier population, or it could be that somehow prescription drugs are used as a substitute for office visits when doctors are less available.

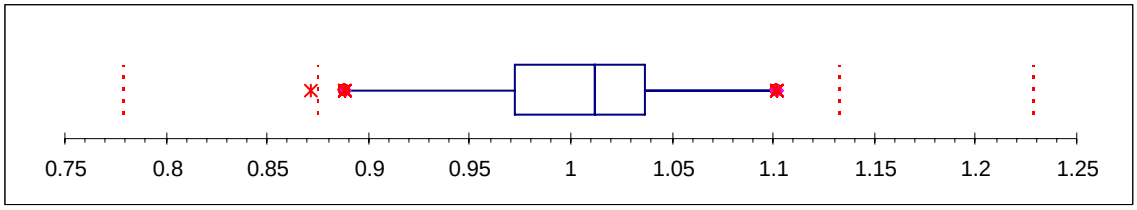
The correlation between the average risk score and the proportion of drug users for each region is .54. However, using the two methods above – comparing the top third of regions to the bottom third and multiple regression – the average risk score for a regon is not significantly related to the proportion of the population using prescription drugs.

Days supplied per user

Having identified little geographic variation in the number of people who fill at least one prescription, we next examine the quantity used by each of the people who did fill a prescription. In this report, we measure quantity in terms of a day's supply of a drug rather than the number of prescriptions. This allows us to capture any variation that might be due to differences in the size of a prescription (e.g. 30 days vs. 90 days).

As shown in Figure 5, the range of variation in median days' supply per person is larger than for the proportion of people with at least one prescription. (Details by region are available in the appendix.) The median number of days of medication supplied per person ranges from a low of 945 days' supply in Hawaii (13% below the national average, an outlier) to a high of 1195 days' supply in the region that includes Indiana and Kentucky (10% above the national average). Regions in the south and Midwest tend to have utilization above the national median, while regions in the west and in New England tend to have utilization below the national median. Hawaii, Alaska, and New Mexico all have utilization more than ten percent below the median of all regions. Correlation between this measure and unadjusted spending is .88.

Figure 5. Variation in Median Days' Supply Per Prescription Drug User, by Region, 2002



We compared health status, demographics, and certain supply factors for the third of regions with the lowest number of days supplied to the third of regions with the highest number of days supplied per user (Figure 6). The results were very similar to the results for the number of users in each region. Regions with a higher number of days supplied had a significantly higher proportion of Medicare enrollees under age 65, a higher proportion of people who smoke, and a higher proportion of individuals with hypertension and diabetes, but a lower proportion of heavy drinkers. People in regions with higher drug use per person were less likely to report that they were in good or better health status.

Again, in a multiple regression controlling for all of these factors, few remain significant. The number of physicians in a region again emerges as significant, with an increase in the number of physicians decreasing the amount of drugs that retirees use.

With both of these methods, the average risk score in each region is significantly related to the number of days supplied per person: regions with higher use also have higher risk scores. However, taken on its own, the average risk score for each region explains only a third of the variation in days' supply. Correlation between days' supply and the average risk score for each region is .58.

Figure 6. Possible Explanatory Factors for Variation in Number of Days' Supply Per Prescription Drug User

	Average of bottom third	Average of top third	t stat: top third vs. bottom third	t stat: multiple regression
Median Days Supply	1017	1142		
Average risk score	97%	100%	**2.42***	**3.05****
% of people living in a metropolitan area	78%	70%	-1.35	1.21
% High school graduate or higher	87%	85%	-1.60	-0.20
HMO Penetration Rate	24%	17%	-1.93	-0.44
Non-Federal Physicians per 100,000 population	276	238	-1.64	**-3.43****
Estimated # Licensed Pharmacists per 1,000 people	11.2	8.3	-1.75	-1.00
% Medicare Enrollees (A &/or B) Under Age 65	14%	17%	**4.11****	0.75
% Medicare Enrollees (A &/or B) Over Age 85	11%	10%	-0.82	1.09
% heavy drinkers	6%	5%	**-3.35****	-1.76
% with asthma	12%	12%	-0.50	1.02
% with high cholesterol	32%	33%	1.16	0.23

% with diabetes	6%	8%	**5.06****	-0.48
% limited by physical, mental or emotional problems	17%	19%	**2.51***	0.91
% reporting good or better health status	86%	83%	**-2.88***	1.58
% with hypertension	23%	28%	**5.84****	0.32
% current smokers	21%	25%	**2.62***	1.59

* Significant at the 5% level ** Significant at the 1% level
Sources for demographic and health status variation are given in the appendix.

Utilization of Selected Drug Classes

Previous studies have found that geographic variation is larger within therapeutic classes of drugs than it is across all classes of drugs. For comparison, we organized the prescriptions in FEP into the classes identified by USP for purposes of Part D formulary development and examined the regional variation in utilization by class. To measure utilization for each class, we measured the average number of days supplied by class and region. The denominator for this average is the number of retirees in the FEP database, who all had some prescription drug utilization. In this section, we review the results for several widely used classes of drugs. Figure 7 presents some summary statistics for these selected classes; the full results by region are available in the appendix.

Consistent with our previous analysis of Express Scripts data, we found that variation in use of individual classes of drugs is greater than the variation in use of all drugs combined, and greater than the variation in many of the other measures included in this report. When considering average days supplied for all drugs, the highest-utilization region has 23 percent more days of medication per user than the lowest-utilization region. Among the twelve specific drug classes we selected, all had greater variation. The smallest difference among the groups we selected was for renin-angiotensin inhibitors and dyslipidemics: the highest-use areas use these drugs about 40 percent more than the lowest-use areas. Use of anti-inflammatory drugs, beta blockers, and gastrointestinal drugs is more than double in the highest-use areas compared to the lowest-use areas. There is a similar pattern for interquartile differences, with much wider differences for individual classes than for drugs overall.

Figure 7. Variation in Use of Selected Drug Classes

	Average Days' Supply Per User - Median of All Regions	Ratio Q3 to Q1	Ratio Max To Min
Anti-Inflammatory	42.1	1.27	2.09
Blood Glucose Regulators	45.5	1.20	1.57
Antidepressants	46.8	1.24	1.65
Cardio/Combos	47.3	1.13	1.82
Respiratory	53.7	1.20	1.50
Gastrointestinal	59.5	1.22	2.12
Cardio/Diuretics	67.7	1.15	1.90
Cardio/Calcium Channel Blockers	70.2	1.18	1.45
Cardio/Renin-Angiotensin	72.1	1.11	1.41
Cardio/Beta Blockers	74.6	1.23	2.13
Cardio/Dyslipidemics	93.1	1.14	1.42
Hormonal Agents	146.5	1.18	1.61
All Drugs	**1121.9**	**1.07**	**1.23**

Variation in use of particular classes of drugs could have two effects. First, higher utilization of particular classes of drugs could contribute to more utilization overall. Second, utilization of more expensive classes of drugs could raise the average cost of a day's supply of medication in a region, even if overall use within that region is average. Each of these could, in turn, lead to higher overall spending. In this section, we focus on the relationship between utilization of each drug class and overall utilization.

As we found in the Express Scripts data, the pattern of geographic variation is quite different from one drug class to another. However, several classes were relatively well correlated with overall drug use (Figure 8): gastrointestinal drugs, anti-inflammatory drugs, blood glucose regulators, antidepressants, and combination cardiovascular drugs all had a correlation of at least .5 with overall utilization. Among the twelve classes we selected, hormonal agents and beta blockers have the lowest correlation with overall drug use. These patterns are quite consistent with the Express Scripts data.

We ran a multiple regression equation to test the significance of utilization for each class in predicting overall utilization. Although beta blockers and hormonal agents have very low correlation with overall drug use, after controlling for use of other drugs, they appear to have a significant relationship with overall drug use. This may be because they are among the most heavily used classes of drugs. Gastrointestinal drugs and calcium channel blockers also have a significant relationship with overall use after controlling for all other classes. These classes are both widely used and more strongly correlated with overall use. As we discuss below, several of the other classes are highly correlated with one another, which may reduce their individual significance in this regression model. Taken together, the regional variation in these twelve classes explains 96 percent of the variation in days' supply per person.

Figure 8. Relationship Between Use of Selected Classes and Use of All Drugs

	Correlation with Days' Supply of All Drugs	t Stat: multiple regression
Cardio/Beta Blockers	0.07	**2.96****
Hormonal Agents	0.08	**4.13****
Cardio/Renin-Angiotensin	0.17	1.49
Cardio/Dyslipidemics	0.23	0.91
Cardio/Diuretics	0.29	0.49
Respiratory	0.44	1.99
Cardio/Calcium Channel Blockers	0.45	**3.84****
Cardio/Combos	0.56	1.22
Antidepressants	0.57	0.92
Anti-Inflammatory	0.65	0.82
Blood Glucose Regulators	0.66	1.44
Gastrointestinal	0.72	**2.32***

* Significant at the 5% level ** Significant at the 1% level

We also looked at the correlation among individual classes of drugs (Figure 9). Not surprisingly, use of many classes of cardiovascular drugs is positively correlated. The exception is the relationship between combination cardiovascular drugs and other cardiovascular drugs. It seems quite likely that in regions where combination drugs are more widely used, they are replacing the use of some other classes of cardiovascular drugs.

There are also relatively high correlations between some classes of drugs that are seemingly unrelated. For example, anti-depressants, anti-inflammatory drugs, and gastrointestinal agents all have correlations with one another of over .70. Hormonal agents have a fairly large negative correlation with many of the classes of cardiovascular drugs.

At the same time, there are many classes whose use is surprisingly uncorrelated, evidence that regional variation in utilization does not happen simply as the result of higher or lower utilization in a region for all classes across the board. Many unrelated classes have low or even negative correlations.

We tested the power of the underlying prevalence of certain diseases in each region for explaining the use of related classes of drugs. For example, we used the prevalence of hypertension and high cholesterol to explain the use of cardiovascular drugs, the prevalence of diabetes to explain the use of blood glucose regulators, and the prevalence of asthma to explain the use of respiratory drugs. The explanatory power of these models was quite low. For most classes of drugs that we tested, the underlying prevalence of the relevant disease explains less than a fifth of the variation in utilization. The exception is calcium channel blockers, for which the prevalence of hypertension and high cholesterol explained almost a third of the variation in use. One possible explanation for the lack of a stronger relationship is the fact that our data on disease prevalence are for the entire population, while the FEP data are only for retirees.

We also ran a model to test the power of a region's average risk score in predicting variation in each of these classes. For most classes, the predictive power of the average risk score was slightly better than that of the prevalence of specific diseases. Again, calcium channel blockers are the class whose use is best predicted by this method: variation in the average risk score predicts nearly three fifths of variation in the use of calcium channel blockers. About a third of the regional variation in the use of cardiovascular drugs overall, cholesterol drugs, and diabetes drugs can be explained with variation in the risk score. For renin-angiotensin inhibitors and beta blockers, the average risk score was significantly predictive, but it explains less than a sixth of the variation.

Figure 9. Correlation of Days' Supply by USP Class

	All Drugs	Anti-depressants	Anti-Inflammatory	Blood Glucose Regulators	Cardio/ Beta Blockers	Cardio/ Calcium Channel Blockers	Cardio/ Combos	Cardio/ Diuretics	Cardio/ Dyslipidemics	Cardio/ Renin-Angiotensin	Gastro-intestinal	Hormonal Agents
Antidepressants	0.57	1.00										
Anti-Inflammatory	0.65	0.71	1.00									
Blood Glucose Regulators	0.66	0.06	0.19	1.00								
Cardio/Beta Blockers	0.07	-0.20	-0.54	0.32	1.00							
Cardio/Calcium Channel Blockers	0.45	-0.23	-0.13	0.62	0.51	1.00						
Cardio/Combos	0.56	0.26	0.69	0.36	-0.49	0.14	1.00					
Cardio/Diuretics	0.29	0.22	-0.18	0.36	0.65	0.19	-0.15	1.00				
Cardio/Dyslipidemics	0.23	-0.25	-0.29	0.52	0.65	0.60	-0.13	0.27	1.00			
Cardio/Renin-Angiotensin	0.17	-0.35	-0.39	0.49	0.65	0.54	-0.21	0.42	0.61	1.00		
Gastrointestinal	0.72	0.82	0.77	0.26	-0.24	-0.12	0.49	0.19	-0.29	-0.33	1.00	
Hormonal Agents	0.08	0.41	0.58	-0.41	-0.83	-0.62	0.36	-0.43	-0.58	-0.61	0.34	1.00
Respiratory	0.44	0.46	0.61	-0.03	-0.58	-0.10	0.41	-0.29	-0.29	-0.54	0.56	0.60

Combining both disease prevalence and the average risk score for each region increases the predictive power of the models somewhat. In all three approaches, the use of beta blockers, diuretics, cardiovascular combination drugs, and respiratory drugs are particularly poorly predicted by these models. It may be that other factors could better explain the use of these drugs.

We note that after controlling for the prevalence of high cholesterol and for the risk score, the prevalence of hypertension in a region is associated with significantly lower use of renin-angiotensin inhibitors and dyslipidemics, while it is associated with increased use of combination cardiovascular drugs. This may have to do with the role of combination drugs for certain patients.

In a final model, we tested the use of each of these selected classes of drugs as a dependent variable of the health status and market variables we have used elsewhere in this report. While the explanatory power of these models is higher, few individual variables stand out as having a significant relationship with utilization of any class. This may be due to the correlation between many of these explanatory variables. We found that after controlling for other factors, regions with a higher number of physicians per capita tend to use more beta blockers and respiratory drugs. Regions with a higher proportion of smokers tend to use more calcium channel blockers. Regions with a higher proportion of the Medicare population that is aged 85 or older tend to use more diuretics and dyslipidemics.

The results of all of these models are available in the appendix.

Discussion: Utilization Factors

Variation in utilization is an important factor in explaining variation in overall spending. In a multiple regression model, the regional variation in the proportion of the population with at least one prescription and in the number of days' supply typically used by those who do fill a prescription together explain about 77 percent of the variation in actual FEP spending. However, only the median days' supply per user is significant. A one day increase in the number of days' supply for each person who uses prescription drugs increases overall spending by about $2 (Figure 10).

Figure 10. Results of a Regression of Overall Spending on Proportion of Population with at Least One Prescription and Median Days' Supply per User

	Coefficients	Standard Error	t Stat
Median days' supply per user	2.16	0.312598	**6.90****
Proportion of population with at least one prescription	216.96	717.5858	0.30

Figure 11 summarizes some of the key variables from this section. There is much more variation in days' supply per user than in the number of users, and it is more closely correlated with overall spending. Days' supply per user can be directly broken up into days' supply for individual drug classes. Variation in the twelve most heavily used drug classes accounts for 96 percent of the variation in overall days' supply per user. Still, there is a great deal of variation in utilization at the class level, and there are not clear patterns in that variation.

Figure 11. Regional Variation in Components of Utilization and Their Correlation with Overall Spending

	Ratio of Q3 to Q1	Ratio of Max to Min	Correlation with Actual Spending
Actual FEP Spending	1.15	1.32	
Proportion of population with at least one prescription	1.02	1.19	0.65
Median days' supply per user	1.07	1.26	0.88
Days' supply per user, selected classes:			
Antidepressants	1.24	1.65	0.50
Anti-Inflammatory	1.27	2.09	0.66
Blood Glucose Regulators	1.20	1.57	0.58
Cardio/Beta Blockers	1.23	2.13	-0.14
Cardio/Calcium Channel Blockers	1.18	1.45	0.45
Cardio/Combos	1.13	1.82	0.59
Cardio/Diuretics	1.15	1.90	-0.02
Cardio/Dyslipidemics	1.14	1.42	0.17
Cardio/Renin-Angiotensin	1.11	1.41	0.03
Gastrointestinal	1.22	2.12	0.69
Hormonal Agents	1.18	1.61	0.15
Respiratory	1.20	1.50	0.57

The failure of our explanatory models to clearly explain variation in use of these individual drug classes raises the possibility that there are unmeasured factors at work. One likely possibility is that regional physician prescribing patterns can vary by class of drug, rather than favoring high or low utilization across all drugs.

Another unexplained factor is the finding that a higher supply of physicians tends to be associated with a decrease in the use of prescription drugs. This is contrary to findings of other studies that have shown that the supply of physicians can increase the use of health services, and may merit further study.

Factors Contributing to Variation: Cost per Day's Supply

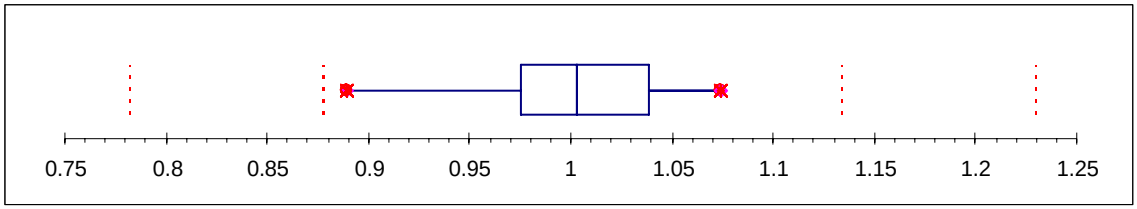
In addition to utilization, the other major component of spending is cost. In this section, we control for utilization by considering the typical cost of one day's supply of a prescription from region to region.[13] We then explore some factors that make up that cost: price for a fixed market basket of drugs, the percentage of prescriptions that are generic drugs, and the use of different classes of drugs.

Overall Cost per Day's Supply

Just as we found variation in utilization in the previous section, we also find variation from region to region in the cost of a day's supply (Figure 12; details by region are available in the appendix). The range of variation is larger than the variation in the number of users, but slightly smaller than the variation in days' supply per user.

The median cost of a day's supply ranges from $1.32 in Wisconsin (11% below the unweighted national average) to $1.60 in Alaska and South Carolina (7% above the national average). Regions in the Midwest and New England tend to have costs per day's supply at or below the national average, while regions in the Southeast tend to have costs at or above the national average. Correlation between the cost of a day's supply and total spending is .56.

Figure 12. Median Cost per Day's Supply, by Region, 2002



[13] Again, we look at the cost of a single day's supply to eliminate any variation that might be due to differing prescription sizes (i.e., 30 vs. 90 days). The cost of a day's supply is calculated as the total spending for each person divided by the prescriptions used by that person and the days' supply included in each prescription. A person using multiple drugs can have more than 365 days' supply in a year.

As we did in the previous section of this report, we compared certain demographic and market factors for the regions with the highest and lowest cost per day's supply of medication (Figure 13). Comparing the top third to the bottom third, regions with higher cost per day have residents that are less likely to have graduated high school, and Medicare enrollees in high-cost regions are more likely to be under 65 and less likely to be over 85. The highest-cost regions have a lower HMO penetration rate and a higher number of drug stores per capita, as well as more independent drug stores.

In a multiple regression controlling for all of these factors, the proportion of Medicare beneficiaries over age 85 remains significant: regions with more of these oldest-old beneficiaries have lower costs. It is possible that while these beneficiaries are more likely to use drugs, the drugs they use are less expensive per dose.

Regions with higher risk scores have higher costs per day's supply, after controlling for other factors. This implies that sicker beneficiaries are not only using more drugs; they are also using a more expensive mix of drugs.

It is notable that the price index for a fixed market basket of drugs is not significantly associated with higher costs per day's supply. Consistent with our finding of very little variation in this measure, this suggests that other measures better explain the variation in costs.

Figure 13. Possible Explanatory Factors for Variation in Cost Per Day's Supply

	Average of bottom third	Average of top third	t stat: top third vs. bottom third	t stat: multiple regression
Median cost per day's supply	1.41	1.57		
Average risk score	0.97	0.99	1.58	**4.87****
% of people living in a metropolitan area	73%	69%	-0.61	0.02
% High school graduate or higher	87%	84%	**-2.27***	-0.68
% Medicare Enrollees (A &/or B) Under Age 65	14%	17%	**2.81***	-2.02
% Medicare Enrollees (A &/or B) Over Age 85	11%	10%	**-4.03****	**-5.66****
Price Index for Third-Party Customers	0.99	1.00	1.57	1.63
HMO Penetration Rate	26%	14%	**-4.08****	-2.05
Non-Federal Physicians per 100,000 population	272	248	-1.06	0.38
Estimated # Licensed Pharmacists per 1,000 people	8.6	8.9	0.51	-1.18
average of total # drug stores per 1,000 people	1.2	1.4	**3.01***	-0.07
%of drug stores that are independent	31%	38%	1.90	**3.36****
average of Mean Annual Pharmacist Wage	77223	76748	-0.30	-0.78
average of Median gross apartment rent (dollars)	573	587	0.35	1.11
% reporting good or better health status	86%	84%	-1.79	0.92

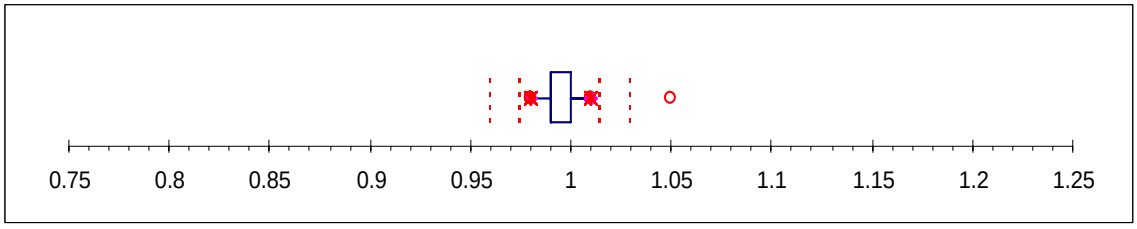
* Significant at the 5% level ** Significant at the 1% level

Sources for demographic and health status variation are given in the appendix.

Price for a Given Market Basket of Drugs

In previous work for ASPE, we examined data from IMS Health's National Prescription Audit™ (NPA™) database for a market basket of 62 drugs (52 brand and 10 generic) commonly used by Medicare beneficiaries.[14] Figure 14 presents these data again, converted into PDP regions for comparison with the other sections of this report (details by region are available in the appendix). We found little evidence that the geographic variation in spending is due to variation in drug prices. Hawaii, at five percent above the national average, is the only region where the price of our market basket of drugs is more than 2 percent away from the unweighted national average. Possibly because of its low variation, this measure has relatively low correlation with the measures we are trying to explain: .17 with overall spending and .28 with overall cost per day's supply.

Figure 14. Variation in Price for a Fixed Market Basket of 62 Drugs, by Region, 2004



Generic Use

There is substantial variation in the share of prescriptions that are dispensed as generics (Figure 15). In Hawaii, only 30 percent of prescriptions are generics (18% below the national average), while in the region composed of Connecticut, Massachusetts, Rhode Island, and Vermont, 46 percent of prescriptions are generics (25% above the national average). This could be due to two factors: people in regions with lower generic dispensing rates may be failing to substitute a generic drug for its brand-name counterpart when it is available, or they may be taking more drugs that have no generic substitutes. We did not attempt to differentiate between these two cases for this project.

The measure of generics as a proportion of all prescriptions has a strong relationship to overall cost per day's supply, as could be expected. The correlation between the two measures is -.95, and generic use explains 90 percent of the variation in cost per day's supply in a regression. Correlation between the generic rate and unadjusted FEP spending is -.59.

[14] We looked at prices for the most common form and strength of each drug during the three months ending June 2004.

Figure 15. Variation in Proportion of Prescriptions that are Generics, by Region, 2002

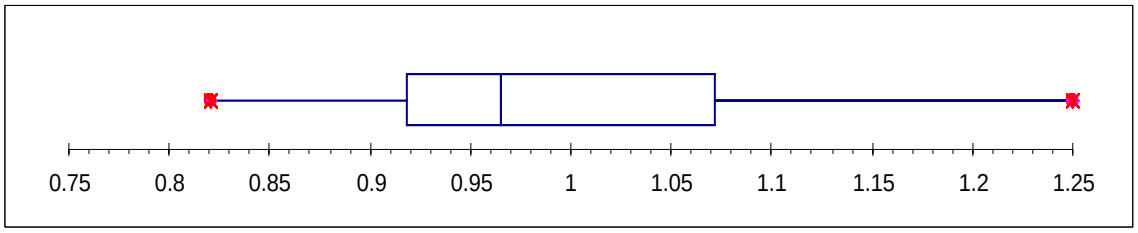


Figure 16 shows possible explanatory factors for this variation, comparing the top third of regions to the bottom third and testing all factors in a regression model. Regions with higher generic use tend to have a higher HMO penetration rate. This seems consistent with the idea that people are more likely to use generics when pushed to do so by a health plan. After controlling for other factors, areas with a higher rate of generic use also tend to have a lower percentage of drugstores that are independent. This is consistent with our previous findings that the presence of chain drug stores tends to lower costs, and suggests that one reason for this effect could be that chain drug stores might be doing a better job encouraging patients to switch to generic drugs.

After controlling for other factors, areas with a higher rate of generic use tend to have lower risk scores. While this is consistent with the result for overall costs, we do not have an obvious explanation for this result. It may be that the risk adjuster implicitly includes the effect of whether generic drugs are available for certain conditions.

Regions with higher generic use also have more Medicare beneficiaries over age 85 and more beneficiaries under 65. The results for these factors are actually in the opposite direction from the results for costs per day's supply. It is unclear why this might be the case.

Figure 16. Possible Explanatory Factors for Variation in Proportion of Prescriptions that are Generic

	Average of bottom third	Average of top third	t stat: top third vs. bottom third	t stat: multiple regression
Median share generic	33%	41%		
Average risk score	1.0	1.0	-1.78	**-4.53****
% of people living in a metropolitan area	72%	74%	0.27	0.50
% High school graduate or higher	84%	87%	2.17	0.79
% Medicare Enrollees (A &/or B) Under Age 65	17%	14%	-1.80	**2.63***
% Medicare Enrollees (A &/or B) Over Age 85	10%	11%	**3.81****	**3.69****
HMO Penetration Rate	16%	28%	**3.25****	**3.05****
Non-Federal Physicians per 100,000 population	243	272	1.33	0.27
Estimated # Licensed Pharmacists per 1,000 people	10.5	8.3	-1.28	0.56
average of total # drug stores per 1,000 people	1.4	1.2	**-2.35***	0.44

%of drug stores that are independent	35%	33%	-0.54	**-3.12****
average of Mean Annual Pharmacist Wage	77799	78655	0.41	0.57
average of Median gross apartment rent (dollars)	600	588	-0.28	-1.68
% reporting good or better health status	83%	86%	**2.40***	-0.65

* Significant at the 5% level ** Significant at the 1% level

Sources for demographic and health status variation are given in the appendix.

Drug Mix

As we did in the previous section, we examined how utilization of selected drug classes is associated with the cost measures we studied. In theory, if high-cost drugs are used at a higher rate, this will raise the typical price of a day's supply of drugs. Similarly, if classes of drugs with no available generics are used at a higher rate, this could be expected to lower the overall utilization of generics as a share of utilization, and raise overall costs.

Our findings (Figure 17) are somewhat consistent with these hypotheses. Utilization levels for some of our selected classes of drugs do seem to be associated with the typical cost of a day's supply. For example, regions with higher use of renin-angiotensin inhibitors have a significantly higher cost per day's supply. This class includes several expensive on-patent medications that could be causing this relationship. Regions with higher use of beta blockers, diurectics, and hormonal agents, on the other hand, tend to have lower costs per day's supply. These classes are composed of older drugs that are generally available as inexpensive generics.

Figure 17. Relationship Between Individual Classes of Drugs and Median Cost per Day's Supply, Proportion of Prescriptions that are Generic, and Overall Spending

	MEDIAN COST PER DAY'S SUPPLY *t*	**% GENERIC** *t Stat: multiple regr*	**FEP SPENDING** *t Stat: multiple r*

	Stat: multiple regression	*session*	*egression*
Antidepressants	-0.38	-0.91	0.77
Anti-Inflammatory	0.18	0.71	-0.71
Blood Glucose Regulators	-0.30	0.28	0.79
Cardio/Beta Blockers	**-3.84*** **	**3.18*** **	-1.41
Cardio/Calcium Channel Block	1.25	-1.61	**4.34*** **

ers			
Cardio/Combos	-0.80	**4.91****	-0.41
Cardio/Diuretics	**-4.30****	**-2.79****	**-2.32***
Cardio/Dyslipidemics	2.07	-1.66	**3.54****
Cardio/Renin-Angiotensin	**2.39***	-1.19	1.87
Gastrointestinal	1.95	**-2.40***	**2.78****
Hormonal Agents	**-2.83****	1.53	1.26
Respiratory	-1.17	1.84	0.79

* Significant at the 5% level **Significant at the 1% level

Some of the results for generic utilization's association with the use of particular drug classes are counterintuitive. For example, the higher use of combination cardiovascular drugs is associated with higher use of generics, even though these combination drugs are primarily on-patent. Likewise,

higher use of diuretics is associated with lower generic use overall, even though most diuretics are generic. We do not have a good explanation for why this might be the case.

We found that despite the counterintuitive result that use of diuretics is associated with lower generic use, regions with higher use of diuretics have significantly lower overall spending. These drugs are among the least expensive, and these results suggest that areas with higher diuretic use may have lower use of more expensive cardiovascular medications. Regions with higher use of calcium channel blockers, anti-cholesterol drugs, and gastrointestinal drugs had significantly higher overall spending. These high-utilization classes include relatively expensive drugs.

Discussion: Cost Factors

Figure 18 summarizes some of the key findings from this section. We established in previous work for ASPE that the variation in drug prices was not likely to be a significant factor in the variation in overall spending. For a fixed market basket of drugs, prices vary little from region to region. Our findings for this report confirm that while the cost for a day's supply of a prescription does vary from region to region, this is not because people are paying significantly different prices for the same prescriptions in different regions.

Instead, the variation in costs appears to be related to the mix of prescriptions. The share of drugs that are dispensed as generic in a given region clearly has a strong impact on the median cost of a day's supply. The regional variation in generic dispensing alone can explain nearly 90 percent of the variation in cost per day's supply. However, it is not clear whether low-generic-use regions are failing to substitute generics when they are available, or whether retirees in these regions are using more drugs that do not have generic substitutes.

Figure 18. Regional Variation in Components of Cost Per Day's Supply and Their Correlation with Overall Spending

	Ratio of Q3 to Q1	Ratio of Max to Min	Correlation with Cost Per Day's Supply	Correlation with FEP Spending
Median cost per day's supply	1.07	1.21		0.56
Prices for a fixed market basket of drugs	1.01	1.07	0.28	-0.17
Median share generic	1.17	1.52	-0.95	-0.53
Days' supply per user, selected classes:				
Antidepressants	1.24	1.65	0.03	0.50
Anti-Inflammatory	1.27	2.09	0.46	0.66
Blood Glucose Regulators	1.20	1.57	0.25	0.58
Cardio/Beta Blockers	1.23	2.13	-0.48	-0.14
Cardio/Calcium Channel Blockers	1.18	1.45	0.24	0.45
Cardio/Combos	1.13	1.82	0.49	0.59
Cardio/Diuretics	1.15	1.90	-0.63	-0.02
Cardio/Dyslipidemics	1.14	1.42	-0.02	0.17
Cardio/Renin-Angiotensin	1.11	1.41	-0.09	0.03

Gastrointestinal	1.22	2.12	0.24	0.69
Hormonal Agents	1.18	1.61	0.16	0.15
Respiratory	1.20	1.50	0.35	0.57

Our findings on the utilization of various classes of drugs suggest that at least part of the issue is related to the use of drugs that do not have generic substitutes. Regions with higher use of diuretics (mostly older drugs with generic substitutes) have significantly lower overall spending. Regions with higher use of calcium channel blockers, anti-cholesterol drugs, and gastrointestinal drugs (newer drugs that are less likely to have generic substitutes) had significantly higher overall spending. It is possible that practice patterns specific to these individual classes of drugs may be having an effect on regional variation in overall spending.

At the same time, cost per day's supply and the proportion of prescriptions that are generic are both significantly related to the HMO penetration rate and the proportion of pharmacies that are independent. Although all the retirees in the FEP data presumably faced the same incentives for generic use, this suggests that at least some of the difference in the generic dispensing rate – and thus overall costs – may also be due to environmental factors that encourage generic substitution when possible.

Comparing Utilization and Cost

Both the median cost for a day's supply and the median number of days' supply are important in explaining regional variation in spending on prescription drugs. In a multiple regression, these two factors together explain 94 percent of the regional variation in spending. Both factors are highly significant. An increase of one day's supply per user increases total per capita spending by about $2. A $1 increase in the cost per day's supply increases total per capita spending by about $866 (Figure 19).

Figure 19. Results of a Regression of Spending per Beneficiary on Days Supplied and Cost Per Day

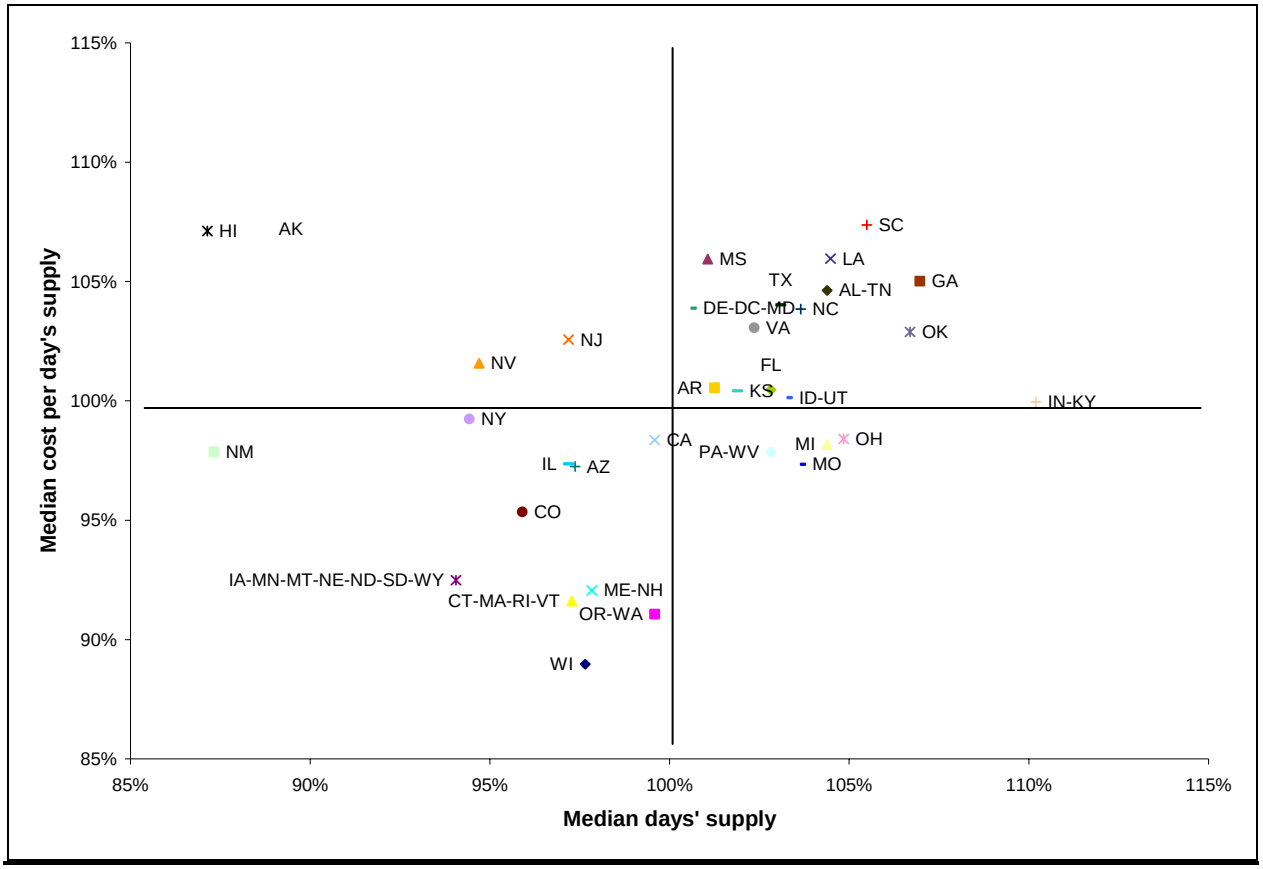
	Coefficient	Standard Error	t Stat
Median cost per day's supply	866.23	88.89	**9.74****
Median days' supply per user	2.05	0.11	**18.62****

In many regions, cost and utilization are working together in the same direction to either raise or lower spending. Figure 20 plots each region in relation to the national average of our main measures of utilization and cost: days' supply per user and cost per day's supply. Many of the PDP regions in the southeast are among those that have above-average utilization and above-average costs for a day's supply. Likewise, the region covering much of the Great Plains, the two New England regions, and a few other western regions, among others, have both below-average utilization and below-average costs for a day's supply.

The apparent outliers are Hawaii and Alaska. These two states have costs per day's supply well above the national average and utilization well below the national average. Despite above-average

costs per day's supply, low utilization means that these two states are among those with the lowest overall spending in the country. This may be a sign that the unique geographic factors in these two states are affecting practice patterns and/or access to prescription drugs.

Figure 20. Days' Supply Per User as a Percent of the National Average vs. Cost Per Day's Supply as a Percent of the National Average



Geographic Variation in Drug utilization and spending Within Regions

The previous sections of this report are concerned with variation *among* PDP regions. We also examined variation *within* PDP regions for some of the measures, to determine whether there are any systematic differences between urban and rural areas. We find mixed results, with different data sources indicating very small differences between urban and rural areas, but in different directions.

Variation Within Regions in Overall Spending

Figure 21 shows the difference in total spending per user between metropolitan and non-metropolitan areas of each region. (Data on the number of users by region and urban/rural status is not available.) On average, per capita spending on prescription drugs by FEP retirees is slightly higher (by about 4 percent) in metropolitan areas than in other parts of the region. Overall, the correlation between spending in regions' metropolitan areas and spending in their non-metropolitan areas is about .86.

In eight regions, spending for FEP retirees in non-metropolitan areas is at least ten percent less per person than spending in metropolitan areas: Alaska, New Mexico, Arizona, Wisconsin, Missouri, the region covering Idaho/Utah, and the region covering Maine/New Hampshire. Although some of these regions are also among the lowest-spending areas, the absolute differences between metro and non-metro spending is also the largest in these regions. At the extreme, rural areas in Alaska have per capita drug spending of only $617, while metropolitan areas have spending of $1,062, by far the largest difference in both absolute and relative terms.[15]

In seven regions the relationship is reversed, with spending slightly lower in non-metropolitan areas. This occurs in Georgia, Hawaii, Louisiana, Illinois, New York, the region covering Delaware/DC/Maryland, and the region covering Pennsylvania/West Virginia. In New York, the region in this group with the largest difference, annual FEP drug spending in non-metropolitan areas is $159 higher per retiree than in metropolitan areas.

The MCBS cannot be divided into regions due to sampling issues, but we did look at the overall difference in spending between metro and non-metro areas. Spending by metro and non-metro beneficiaries in the MCBS is very close – less than a 1 percent difference – but the small difference is in the opposite direction from the difference we found in the FEP data, with rural areas spending slightly more than metropolitan areas.

[15] After excluding Alaska from the results as an outlier, the difference between metro and non-metro areas persists, but is slightly smaller: 3 percent instead of 4 percent.

Figure 21. Median Drug Expenditures Per User, Metro vs. Non-Metro, By Region

PDP Region	States	Whole Region	Non-metro	Metro	Non-metro as % of Metro
04	NJ	$1,336.37		$1,336.37	
34	AK	$ 947.65	$ 617.47	$1,061.81	0.58
26	NM	$1,091.99	$ 1,003.16	$1,164.09	0.86
16	WI	$1,155.01	$ 1,046.39	$1,197.44	0.87
28	AZ	$1,269.31	$ 1,122.91	$1,290.63	0.87
31	ID-UT	$1,429.21	$ 1,276.73	$1,459.49	0.87
01	ME-NH	$1,245.16	$ 1,156.11	$1,283.19	0.90
18	MO	$1,416.21	$ 1,299.18	$1,450.41	0.90
25	IA-MN-MT-NE-ND-SD-WY	$1,155.59	$ 1,095.21	$1,203.13	0.91
19	AR	$1,389.69	$ 1,319.28	$1,441.11	0.92
09	SC	$1,565.06	$ 1,478.89	$1,585.30	0.93
23	OK	$1,554.56	$ 1,480.32	$1,594.67	0.93
24	KS	$1,423.32	$ 1,357.56	$1,457.83	0.93
29	NV	$1,263.39	$ 1,183.10	$1,275.87	0.93
13	MI	$1,397.20	$ 1,352.83	$1,416.98	0.95
22	TX	$1,482.53	$ 1,417.47	$1,493.55	0.95
11	FL	$1,461.40	$ 1,407.99	$1,465.55	0.96
30	OR-WA	$1,214.47	$ 1,183.51	$1,228.50	0.96
32	CA	$1,326.48	$ 1,272.31	$1,329.30	0.96
20	MS	$1,472.31	$ 1,447.32	$1,494.40	0.97
27	CO	$1,249.26	$ 1,220.12	$1,255.24	0.97
15	IN-KY	$1,555.25	$ 1,535.60	$1,560.36	0.98
02	CT-MA-RI-VT	$1,213.67	$ 1,207.81	$1,214.19	0.99
07	VA	$1,473.59	$ 1,456.85	$1,476.70	0.99
12	AL-TN	$1,555.13	$ 1,537.78	$1,560.08	0.99
14	OH	$1,434.67	$ 1,425.14	$1,436.69	0.99
08	NC	$1,506.40	$ 1,502.86	$1,507.08	1.00
05	DE-DC-MD	$1,449.96	$ 1,499.80	$1,447.33	1.04
10	GA	$1,575.40	$ 1,643.07	$1,562.97	1.05
06	PA-WV	$1,387.03	$ 1,459.85	$1,368.13	1.07
33	HI	$1,138.42	$ 1,210.25	$1,135.31	1.07
21	LA	$1,545.97	$ 1,648.50	$1,524.88	1.08
17	IL	$1,254.37	$ 1,350.15	$1,239.30	1.09
03	NY	$1,207.20	$ 1,350.29	$1,190.81	1.13
Average		$1,357.15	$ 1,320.18	$1,373.78	0.96

Within Region Variation in Utilization

We also examined the within-region variation in the days' supply used by the FEP retirees in our database of those who had at least one prescription (Figure 22). On this measure, there is even less variation between metropolitan and non-metropolitan areas than there is in spending overall. On average, the number of days of medication supplied per person is slightly higher (by about 2%) in metropolitan areas than in non-metropolitan areas. The correlation between metro and non-metro areas is about 77%.

In the previous section, we found several regions with overall spending in their non-metropolitan regions that is ten percent below metropolitan spending. In contrast, no region has non-metropolitan utilization ten percent below its metropolitan utilization. The region with the largest difference in this direction is the region covering Idaho and Utah. Metropolitan areas in this region have median utilization of 1102 days' supply per person, while non-metropolitan areas have utilization of just 999 days' supply per person, a nine percent difference. The difference in New Mexico is also nine percent, but smaller in absolute terms.

The seven regions that break the norm by having lower spending in metropolitan areas also have lower utilization in metropolitan areas, as does Mississippi. New York is again the region with the largest difference, with statistics almost the opposite of Idaho and Utah's. Metropolitan areas in New York have median days' supply of just 990 days per person, while non-metropolitan areas have median utilization of 1100 days' supply per person.

In the MCBS, we were able to calculate the number of prescriptions used per person. Again, the direction of the difference in the MCBS is different from the direction of the difference in the FEP data. The MCBS shows metropolitan beneficiaries using a median of 21 prescriptions per year, while non-metropolitan beneficiaries used a median of 23 prescriptions per year. As discussed in previous sections, this does not take into account possible differences in the days of medication supplied in each prescription. However, it is consistent with the MCBS finding of slightly more spending by non-metropolitan beneficiaries.

Figure 22. Median Days' Supply, Metro vs. Non-Metro, By Region

PDP Region	States	Whole Region	Non-metro	Metro	Non-metro as % of Metro
04	NJ	1054		1025	
26	NM	947	860	947	0.91
31	ID-UT	1120	999	1102	0.91
19	AR	1098	1013	1087	0.93
18	MO	1124	1044	1108	0.94
23	OK	1157	1070	1140	0.94
25	IA-MN-MT-NE-ND-SD-WY	1020	950	1010	0.94
27	CO	1040	951	1010.5	0.94
29	NV	1027	930	985.5	0.94
32	CA	1080	975	1039	0.94
01	ME-NH	1061	990	1038	0.95
09	SC	1144	1059	1115.5	0.95
30	OR-WA	1080	1003.5	1057	0.95
34	AK	963	924	971	0.95
22	TX	1118	1046.5	1090	0.96
08	NC	1124	1076	1104.5	0.97
13	MI	1132	1072	1110	0.97
28	AZ	1056	990	1020	0.97
11	FL	1115	1062	1080	0.98
12	AL-TN	1132	1082	1103	0.98
15	IN-KY	1195	1158.5	1170	0.99
24	KS	1105	1070	1077	0.99
07	VA	1110	1080	1080	1.00
14	OH	1137	1107	1106	1.00
16	WI	1059	1027	1027	1.00
02	CT-MA-RI-VT	1055	1031.5	1025	1.01
10	GA	1160	1136.5	1118	1.02
20	MS	1096	1075.5	1052	1.02
21	LA	1133	1112	1095	1.02
05	DE-DC-MD	1091	1113	1070	1.04
17	IL	1054	1059	1019	1.04
06	PA-WV	1115	1133	1080	1.05
03	NY	1024	1100	990	1.11
33	HI	945	1020	920.5	1.11
average		1084.441	1040	1058.015	0.98

Discussion: Spending Variation Within Regions

The differences in results between data sets – and the small magnitude of the differences between urban and rural in each data set – suggest that nationally, there is not a large difference between urban and rural spending for prescription drugs. Some individual regions have a notable difference between urban and rural utilization and spending, but the pattern is not consistent enough nationwide to make metropolitan status a promising basis for fine-tuning payments to prescription drug plans. This is consistent with our findings in previous sections, which never found that the proportion of a region's population living in metropolitan areas to be a significant explanatory factor for spending or utilization.

Conclusion

This study looked at geographic variation for a retired population with employer-sponsored coverage using a single benefit design. It characterizes spending prior to the introduction of the Medicare Part D benefit, with utilization patterns that arise from a different benefit design than the Part D benefit. It does not incorporate factors, such as differences in benefit design or insurance coverage, that might lead to even greater geographic variations for a broader population.

Even with this shared benefit design, there is a notable amount of spending variation from region to region that is not explained by the risk adjuster. We have examined several components of that variation and found variation in both per capita drug utilization and the mix of drugs that are used. However, the results do not lead to a clear conclusion that would support specific adjustments to the federal payments to drug plans to address this geographic variation.

Nevertheless, the variation has potentially serious implications for beneficiaries. To the extent that geographic variation in spending is not accounted for by variables that are factored into plan payments, beneficiaries in areas with higher utilization will likely pay higher premiums for drug coverage under Part D over time. As reported in the Addendum to this Chapter below, we found that Part D plans are varying their premiums from region to region. While this is probably due in part to market competition factors, such as the degree of competition from Medicare Advantage plans, it may also be an indication that these plans expect some continued geographic variation in utilization.

Ideally, utilization data from Part D plans can be used to study these questions further before the Department must submit its findings to Congress in 2009. There are several issues that could be investigated to further clarify the issues driving the geographic differences in utilization and spending. The median number of days' supply was the more important measure of utilization that we studied. Another topic for possible further investigation is the regional variation in high users of prescription drugs. It may be that a concentration of users of large numbers of prescriptions could affect overall spending, without being picked up in the median of drug use.

We began to break days' supply into individual drug classes, and found even more variation by class than in days' supply overall. This line of inquiry seems particularly fruitful for future study. It may be that physician practice patterns vary regionally at the level of drug class. The classes that have disproportionately high costs or a large number of users can have a particularly important effect on overall utilization and spending.

The proportion of prescriptions that are generic explains a great deal of the variation in cost. We did not fully explore the possible causes for the large variation in this factor. Potential further research could investigate whether variation appears to be due to the use of drugs that have no generic substitutes vs. failure to substitute generics when they are available. Further research could also determine whether state laws promoting or restricting generic substitution at the pharmacy seem to be playing a role.

After controlling for the average risk score in each region, we also found non-health factors that were significantly associated with costs and utilization. A higher supply of physicians per capita is associated with lower drug utilization. Higher penetration by HMOs and chain drug stores are associated with higher generic use and lower drug costs. These are all results that invite further investigation into the larger market dynamics of the prescription drug system.

Addendum: Geographic Variation in Part D Premiums

Our previous work for ASPE suggested that if geographic variation in utilization of Part D drug spending is not accounted for by the risk adjustment mechanism, beneficiaries in high-utilization states would pay more for Part D coverage than beneficiaries in low-utilization states. The PDP premiums for 2006 allow us to examine whether plans seem to expect systematic geographic differences in spending and thus set premiums that vary from region to region.

The Medicare Modernization Act authorized the Secretary to make adjustments if there was evidence that drug prices varied geographically. Both the analysis by price data we did for ASPE and analysis by CMS found only minimal variation; thus, no adjustments were made for 2006. The MMA also calls for the Secretary to study whether drug utilization varies geographically. For that report, due in 2009, the Secretary must distinguish spending variation attributable to price variations versus that due to differences in utilization. The report will also include recommendations on possible changes to the geographic risk adjustment factor to take utilization into account.

Premium differences by region give us an early opportunity look at this question. Some differences could result from market factors, but expected utilization is likely to be a major factor when plans set different premiums for the same benefit in different regions.

Approach

In this memo, we examine the premiums charged by fourteen organizations. These include the ten organizations approved by CMS as national plans as well as four plans (Sterling, United American, Humana, and Pennsylvania Life) that are in all but two or three regions.[16] To standardize the analysis, we considered only the least expensive option from each company. For all but one of the companies in this analysis, the lowest-premium plan is either a standard benefit package or a package that is actuarially equivalent to the standard package.[17] We also created an index that averages the 14 plans' premiums for this basic benefit package in each region. In addition, CMS provided an average of all premiums for each PDP region, which includes both basic and enhanced packages. We have included this as an additional index.

In our analysis, we compare variation in actual premiums to three measures calculated using FEP data from 2002: actual (unadjusted) FEP spending, projected risk adjusted spending, and predicted premiums. Unadjusted plan spending includes the amounts paid by BCBS (the plan) in 2002 but excludes enrollee cost sharing, as provided on the original FEP file. Risk-adjusted projected plan spending includes only the estimated payments a plan would make under the Part D benefit, taking into account the impact of the deductible, initial coverage period, coverage gap, catastrophic coverage, and overhead expenses. This measure is inflated to reflect projected 2006 prices and then adjusted to account for the case mix of the enrollees in each state, as measured by the CMS risk-adjustment model (January 2005 version). Accounting for benefit design and case mix in this way reduces geographic variation, but a substantial amount of variation remains.

We estimated projected beneficiary premiums for each region based on the formula specified in law. For the standard benefit, enrollees must pay a base national premium plus the difference between their plan's bid and the nationwide average of bids. We used risk-adjusted plan spending as a proxy for the bid of a plan in a given state, and risk-adjusted national spending as a proxy for the nationwide average. The variation in the projected beneficiary premiums is greater than for the spending measures.

We found that plans do expect geographic differences in spending: none of the fourteen plans offers the same premium nationwide. However, most plans show less variation in their premiums than we had predicted based on FEP data. In addition, plans vary in their assessment of which regions will be more or less expensive than average. Some general trends found in the FEP data still hold: some areas in the southeast tend to be more expensive, and some areas of the west tend to be less expensive. Regions with higher Medicare Advantage penetration tend to have lower premiums.

Premium variation is generally not as large as predicted by FEP data, but it varies by plan.

[16] Pennsylvania Life is one of several organizations selling plans under the trade name of Prescription Pathway. Premiums are nearly identical across the different organizations in a given region. We use Pennsylvania Life as a proxy for all Prescription Pathway plans.

[17] The one exception is Coventry AdvantraRx Value, which uses an enhanced benefit package. The MMA requires that each organization offer one plan that is a standard or alternative benefit design. Coventry's alternative benefit plan is its highest-premium plan.

In absolute terms, the difference between the highest-priced region and the lowest-priced region ranges from $5 a month in Coventry's AdvantraRX Value plan to about $16 in Humana's Standard plan (Figure 1). The range in the index of premiums for the 14 plans we looked at is about $9.[18] The range in the CMS index of all plans is slightly larger, possibly because of the wider variation in plans included.[19] None of the plans had a dollar range as large as the one predicted by FEP data ($23).

Plan premiums vary geographically not only in the absolute level of premiums but also in terms of the relative range of premiums offered across regions. For the index of 14 plans, the highest-cost region is 12% above the median (11% for the index of all plans). CIGNA charges beneficiaries in their highest cost region only 7% above their median premium. Four plans charge beneficiaries in their highest-cost region more than 30% of the median premium, with Humana's at 74% of the median.[20] These four are higher than the percentage difference predicted by the FEP data (21%).[21]

Figure 1. Range of Premiums in 14 PDPs and Premiums Predicted with FEP Data

	Median Monthly Premium	Range	% maximum is above median
Coventry AdvantraRX Value	$20.96	$5.00	11%
CIGNA HealthCare	$34.84	$6.98	7%
Community Care Rx Basic	$30.84	$7.06	8%
United Healthcare – AARP	$26.44	$7.33	14%
Medco Prescription Savings Plan	$31.94	$8.44	11%
Pennsylvania Life Standard Defined Reg	$30.77	$9.53	10%
SilverScript	$28.88	$9.71	16%
United American Medicare Drug Plan	$34.92	$11.18	17%
Aetna Medicare Prescription Basic Plan	$34.17	$11.36	14%
Sterling Prescription Drug Plan	$54.40	$11.83	12%
Unicare - Medicare RX Rewards	$22.75	$14.12	38%
WellCare Signature	$24.47	$15.60	34%
PacifiCare Saver Plan	$26.63	$15.86	31%
Humana PDP Standard	$10.29	$16.04	74%
Index of 14 plans	$29.38	$9.03	12%
CMS index of all plans	$33.07	$11.45	11%
FEP Projected Premium	$43.46	$23.09	21%

[18] To create the index, we calculated an average of the 14 premiums for each PDP region. The index value (or average of the 14 premiums) in the most expensive region is $32.90, and the index value in the least expensive region is $23.87.

[19] The index of all plan premiums was calculated by CMS. It represents an unweighted average of all plan premiums, including both basic benefit packages and enhanced packages.

[20] Although Humana's premiums show a larger range than any other plan in both relative and absolute terms, the median premium is lower than any other plan. Even Humana's highest premiums are lower than many other plans' premiums.

[21] The analysis of FEP data was not designed to predict the level of the premiums, only the relative variation by state and region. Thus, this comparison is more relevant than the absolute dollar range.

Figure 2. Range of Premiums in 14 PDPs and Premiums Predicted with FEP Data

Figure 2 provides plots of the variation. In each plot, the center line represents the median of the distribution of each plan's premiums. The box surrounding the median represents the central 50 percent of premiums – the interquartile range. The lines extending to the left of the box represent the lowest and highest quartile of premiums.

On average, premiums correlate with FEP data -- but some plans are quite different.

Most plans show premium variation that is correlated with FEP data (Figure 3). However, there is wide variation in the level of association with FEP. Because CMS provided potential bidders some access to the FEP data, some plans may have used these data to help set different regional premiums. In most cases, plan premiums have a stronger correlation with unadjusted spending than with a risk-adjusted measure of spending. This may be a coincidence, or it may reflect some underlying assumptions about risk adjustment and the beneficiaries these plans expect to enroll. Compared with other plans, Sterling, Medco, and Aetna's premiums have relatively low correlations with either measure. Additional investigation would be required to understand what factors are driving these differences across plans.

Figure 3. Premium Correlation with FEP Data, by Plan

	Correlation with Unadjusted FEP Spending	Correlation with Risk Adjusted FEP spending
Coventry AdvantraRX Value	0.499	0.404
WellCare Signature	0.311	0.661
Unicare - Medicare RX Rewards	0.683	0.620
PacifiCare Saver Plan	0.402	0.662
United Healthcare – AARP	0.738	0.785
SilverScript	0.852	0.650
Community Care Rx Basic	0.627	0.297
Medco Prescription Savings Plan	0.224	0.325
Aetna Medicare Prescription Basic Plan	0.173	0.251
CIGNA HealthCare	0.496	0.180
Sterling Prescription Drug Plan	0.361	0.086
United American Medicare Drug Plan	0.705	0.695
Humana PDP Standard	0.582	0.495
Pennsylvania Life Standard Defined Reg	0.976	0.847
Index of 14 plans	0.642	0.660
CMS Index of all plans	0.536	0.528
FEP Projected Premium	0.788	1.000

Note: correlation for each plan is calculated across the PDP regions (n=34). Four plans cover fewer than all 34 regions: Sterling, United American, Humana, and Pennsylvania Life.

On average, premiums are higher in the southeast, and lower in the west and northeast – but few PDP regions are consistently high or low.

Figure 4 shows PDP regions ranked from least expensive to most expensive, using the index of 14 plans. In general, when premiums are averaged in this way, regions in the west and northeast tend to be less expensive, while states in the southeast are more expensive. This is consistent with our findings for FEP data.

When we looked at the ranking of the 34 PDP regions in the distribution of premiums for each of the 14 plans individually, we found that this general picture glosses over a great deal of variation at the plan level. Over half of the regions show up in the most expensive quartile of one plan's premiums and in the least expensive quartile of another plan's premiums. This indicates a substantial amount of disagreement among plans about expected costs in each region. But, as described below, the pattern by plan does match in broad outlines the pattern for the plan averages with lower premiums in western states and higher premiums in the southeast.

Five PDP regions are consistently inexpensive enough that they are never in the highest quartile of any plan's premiums: New Mexico (Region 26), Colorado (Region 27), Nevada (Region 29), California (Region 32), and Hawaii (Region 33). However, no region is consistently less expensive than the median in all of the 14 plans we examined.

Eight PDP regions are consistently expensive enough that they are never in the cheapest quartile for any of the 14 plans: Mississippi (Region 20), Louisiana (Region 21), North Carolina (Region 8), South Carolina (Region 9), Indiana/Kentucky (Region 15), Missouri (Region 18), Oklahoma (Region 23), and Kansas (Region 24). Of these, Louisiana and North Carolina are consistently more expensive than the median of each of the 14 plans' premiums.

Figure 4. Average Plan Premiums by PDP Region

Region	States Included	Average of 14 plans	Ratio to median	Average of all plans (CMS)	Ratio to median
32	CA	$23.87	0.81	$25.41	0.77
26	NM	$26.81	0.91	$29.02	0.88
3	NY	$26.82	0.91	$32.45	0.98
28	AZ	$27.22	0.93	$28.08	0.85
29	NV	$27.23	0.93	$30.32	0.92
30	OR/WA	$27.37	0.93	$30.05	0.91
33	HI	$27.38	0.93	$27.44	0.83
2	CT/VT/MA/RI	$27.71	0.94	$30.53	0.92
27	CO	$27.82	0.95	$28.52	0.86
25	IA/MN/NE/SD/ND/WY/MT	$28.00	0.95	$32.86	0.99
17	IL	$28.31	0.96	$31.85	0.96
16	WI	$28.33	0.96	$31.49	0.95
4	NJ	$28.54	0.97	$32.09	0.97
11	FL	$28.79	0.98	$33.01	1.00
14	OH	$29.08	0.99	$32.89	0.99
5	DE/DC/MD	$29.18	0.99	$33.63	1.02
6	PA/WV	$29.32	1.00	$32.78	0.99
7	VA	$29.43	1.00	$34.19	1.03
31	ID/UT	$29.52	1.00	$33.65	1.02
34	AK	$29.83	1.02	$34.66	1.05
22	TX	$29.84	1.02	$32.63	0.99
24	KS	$29.94	1.02	$33.12	1.00
18	MO	$29.98	1.02	$33.30	1.01
12	AL/TN	$30.30	1.03	$33.29	1.01
19	AR	$30.40	1.03	$35.45	1.07
13	MI	$30.40	1.03	$33.22	1.00
1	ME/NH	$30.95	1.05	$35.69	1.08
10	GA	$30.97	1.05	$33.17	1.00
23	OK	$31.49	1.07	$35.75	1.08
9	SC	$31.67	1.08	$34.89	1.06
20	MS	$31.80	1.08	$36.39	1.10
8	NC	$32.40	1.10	$36.86	1.11
15	IN/KY	$32.53	1.11	$35.85	1.08
21	LA	$32.90	1.12	$36.85	1.11

Regions with more Medicare Advantage penetration tend to have lower premiums.

For most plans, there is an association between Medicare Advantage penetration and the premiums the plan offers. We considered relationships with both the totally number of MA plans that offered competition in a given market as well as the proportion of the beneficiary population enrolled in MA plans. In nearly every case, the correlation to enrollment was higher. This might suggest that the presence of available plans is less important if beneficiaries have not demonstrated their interest in joining these plans. Our previous work for ASPE showed that states with higher managed care penetration tend to have lower drug spending overall. Thus, it is not clear whether the association between Medicare Advantage penetration and lower PDP premiums is directly a result of PDPs trying to compete with MA plans, or whether it simply reflects lower costs in these areas.

Figure 5. Premium Correlation with Medicare Advantage Penetration, by Plan

	Correlation with Average Number of MA contracts, 2005	Correlation with % of Medicare beneficiaries enrolled in MA
United American Medicare Drug Plan	-0.333	-0.592
Community Care Rx Basic	0.068	-0.568
CIGNA HealthCare	0.019	-0.511
Sterling Prescription Drug Plan	0.105	-0.498
Unicare - Medicare RX Rewards	-0.246	-0.487
Medco Prescription Savings Plan	-0.109	-0.476
PacifiCare Saver Plan	-0.439	-0.472
Coventry AdvantraRX Value	-0.167	-0.452
Pennsylvania Life Standard Defined Reg	-0.327	-0.447
Humana PDP Standard	-0.201	-0.430
Aetna Medicare Prescription Basic Plan	-0.513	-0.429
United Healthcare - AARP	-0.205	-0.401
SilverScript	-0.088	-0.344
WellCare Signature	-0.502	-0.325
Index of 14 plans	-0.452	-0.718
CMS Index of all plans	-0.305	-0.804
FEP Projected Premium	-0.411	-0.469

Explaining Regional Variation in Premiums

The data reported here show that there are clear regional variations in the premiums charged by plans for Medicare Part D. The pattern of variation varies by plan, although there are some consistencies. Where patterns do exist – with lower premiums in the West and higher premiums in the Southeast – they appear to be consistent with our previous findings of underlying differences in utilization in these areas. One possibility is that some regional differences in health status are not captured adequately by the risk adjusters, and plans are trying to protect themselves against these cost differences. To the extent this is the case, future work in this project may reveal potential improvements to the risk adjusters. Another possibility is that there are regional differences in the

prescribing patterns of physicians in different parts of the country. It is unclear whether differences of this sort should be part of the risk adjusters or whether the differences should offer incentives for changes in prescribing patterns.

Because the Medicare drug benefit is new, simpler explanations for premium variations may suffice. All players in the system are being forced to make decisions with incomplete information. Because plans had access to some of the FEP data prior to setting their premiums, some may have used these results to set premiums in different regions, while other plans may have relied on internal analyses of their own data and different results.

In addition, the competitive environment may have been a factor. As suggested by the correlation with Medicare Advantage penetration, plans could be setting premiums lower in areas where more competition from MA plans was a factor. And there could be other competitive factors that are not readily evident. Even though the market for stand-alone PDPs is largely dominated by national organizations, the presence of a strong local competitor (e.g., a Blue Cross plan) could lead plans to set a lower premium to ensure a good market share. Finally, it is quite possible that there will be significant shifts in the pattern of premiums across regions from the first year to future years as data on drug use under the new benefit becomes available. Further research is needed to understand better the regional premium variations. But it is clear that they are a significant part of the marketplace for the new benefit.

Conclusions on Variation in Premiums

As the Medicare Part D drug benefit is implemented, the immediate interest of policymakers is whether adequate enrollment is achieved and whether those who enroll are able to navigate the new system successfully and obtain the drugs they need. The purpose of this memo is to look at an issue that may be initially under the radar: geographic variation in the premiums charged by Part D plans. There are potential political implications when beneficiaries in one part of the country pay more for the same benefits than their counterparts elsewhere.

Our analysis shows that premiums do vary substantially from region to region. Premiums tend to be lower in the west and in regions with higher Medicare Advantage penetration and are higher in the southeast. Overall, the pattern of premiums has a fairly strong correlation with the drug utilization patterns we previously found with FEP data, although this correlation is considerably stronger for some organizations offering drugs plans nationally than for others.

Future work under way for ASPE will examine in greater depth how patterns of utilization vary geographically and whether there are clear explanations for this variation. In addition, plans will make new decisions each year on what premiums to charge – and whether to increase or decrease premium differences from region to region. Local competition could lead to premium differences that are not related to utilization differences. By 2009, when the Secretary is required to report on geographic variation in drug utilization, we should have considerably more evidence available on which to base a recommendation for whether other adjustments are necessary.

Appendix to Chapter 3

Figure A-1. Utilization and Cost Factors, by Region

PDP Region	States	Actual FEP Spending	Risk Adjusted Plan spending (FEP)	% with at least one prescription	Median days' supply	Median cost per day's supply	Price Index for Third-Party Customers	Median share generic
01	ME-NH	1658	1547	93%	1061	1.37	0.98	43%
02	CT-MA-RI-VT	1638	1515	92%	1055	1.36	1.01	46%
03	NY	1619	1434	88%	1024	1.48	0.99	37%
04	NJ	1795	1530	91%	1054	1.53	0.99	35%
05	DE-DC-MD	1925	1631	92%	1091	1.55	0.99	33%
06	PA-WV	1845	1560	92%	1115	1.46	0.99	39%
07	VA	1928	1650	93%	1110	1.53	0.99	35%
08	NC	1930	1699	93%	1124	1.55	0.99	35%
09	SC	2002	1668	93%	1144	1.60	0.99	32%
10	GA	2011	1682	93%	1160	1.56	1.00	34%
11	FL	1862	1585	93%	1115	1.50	0.99	35%
12	AL-TN	1982	1706	94%	1132	1.56	1.01	33%
13	MI	1850	1588	91%	1132	1.46	0.98	40%
14	OH	1853	1606	92%	1137	1.46	0.99	38%
15	IN-KY	1990	1705	93%	1195	1.49	0.99	37%
16	WI	1544	1540	91%	1059	1.32	1.00	44%
17	IL	1676	1585	91%	1054	1.45	1.00	39%
18	MO	1826	1643	93%	1124	1.45	0.99	40%
19	AR	1826	1652	93%	1098	1.50	1.01	36%
20	MS	1937	1688	93%	1096	1.58	1.01	33%
21	LA	1967	1652	92%	1133	1.58	1.01	33%
22	TX	1918	1658	92%	1118	1.55	0.99	33%
23	OK	1996	1711	93%	1157	1.53	0.99	35%
24	KS	1843	1658	92%	1105	1.49	0.99	35%
25	IA-MN-MT-NE-ND-SD-WY	1587	1582	91%	1020	1.38	1.00	40%
26	NM	1551	1542	90%	947	1.46	0.99	40%
27	CO	1714	1633	92%	1040	1.42	0.99	41%
28	AZ	1671	1568	90%	1056	1.45	0.99	39%
29	NV	1707	1564	90%	1027	1.51	0.99	35%
30	OR-WA	1679	1599	92%	1080	1.36	0.99	42%
31	ID-UT	1842	1691	93%	1120	1.49	0.99	35%
32	CA	1779	1595	92%	1080	1.46	0.99	40%
33	HI	1604	1484	87%	945	1.59	1.05	30%
34	AK	1528	1558	79%	963	1.60	1.00	33%
Unweighted national average		1797	1609	91%	1084	1.49	1.00	37%

Figure A-2. Utilization and Cost Factors as a Percent of the National Average, by Region

PDP Region	States	Actual FEP Spending -	Risk Adjusted	% with at least one	Median days as %	Median cost as % of	Price Index for Third-	Median share

		% of national	Plan spending (FEP) - % of national average	prescription - % of national average	of average	national average	Party Customers	generic as % of average
01	ME-NH	92%	96%	101%	98%	92%	0.98	118%
02	CT-MA-RI-VT	91%	94%	100%	97%	92%	1.01	125%
03	NY	90%	89%	96%	94%	99%	0.99	101%
04	NJ	100%	95%	100%	97%	103%	0.99	95%
05	DE-DC-MD	107%	101%	101%	101%	104%	0.99	89%
06	PA-WV	103%	97%	100%	103%	98%	0.99	105%
07	VA	107%	103%	101%	102%	103%	0.99	96%
08	NC	107%	106%	102%	104%	104%	0.99	95%
09	SC	111%	104%	101%	105%	107%	0.99	86%
10	GA	112%	105%	102%	107%	105%	1.00	91%
11	FL	104%	99%	102%	103%	100%	0.99	94%
12	AL-TN	110%	106%	103%	104%	105%	1.01	90%
13	MI	103%	99%	100%	104%	98%	0.98	107%
14	OH	103%	100%	100%	105%	98%	0.99	102%
15	IN-KY	111%	106%	102%	110%	100%	0.99	101%
16	WI	86%	96%	99%	98%	89%	1.00	119%
17	IL	93%	99%	99%	97%	97%	1.00	106%
18	MO	102%	102%	102%	104%	97%	0.99	108%
19	AR	102%	103%	101%	101%	101%	1.01	97%
20	MS	108%	105%	102%	101%	106%	1.01	90%
21	LA	109%	103%	101%	104%	106%	1.01	90%
22	TX	107%	103%	101%	103%	104%	0.99	91%
23	OK	111%	106%	102%	107%	103%	0.99	95%
24	KS	103%	103%	101%	102%	100%	0.99	95%
25	IA-MN-MT-NE-ND-SD-WY	88%	98%	100%	94%	92%	1.00	109%
26	NM	86%	96%	99%	87%	98%	0.99	108%
27	CO	95%	101%	101%	96%	95%	0.99	111%
28	AZ	93%	97%	99%	97%	97%	0.99	105%
29	NV	95%	97%	99%	95%	102%	0.99	94%
30	OR-WA	93%	99%	100%	100%	91%	0.99	113%
31	ID-UT	103%	105%	102%	103%	100%	0.99	94%
32	CA	99%	99%	100%	100%	98%	0.99	107%
33	HI	89%	92%	95%	87%	107%	1.05	82%
34	AK	85%	97%	87%	89%	107%	1.00	90%

Figure A-3. Average Days' Supply for Selected Classes of Drugs, by Region

Region	Anti-depressants	Anti-inflammatory	Blood glucose regulators	Cardio/ Beta blockers	Cardio / calcium channel blockers	Cardio / diuretics	Cardio / dyslipidemics	Cardio / renin-angiotensin	Cardio / combos	Gastro-intestinal	Hormonal agents	Respiratory
1	52.92	36.86	45.50	102.71	65.86	78.23	107.79	73.49	31.39	57.60	118.32	49.02
2	44.57	30.97	44.15	105.88	71.56	79.49	101.54	75.51	31.67	55.04	110.96	44.36
3	37.87	29.31	45.42	95.33	76.66	68.27	93.67	81.90	38.36	48.71	116.99	42.30
4	35.12	29.94	54.34	88.51	80.17	66.75	102.92	79.01	45.10	50.38	110.49	43.37
5	39.40	39.38	55.32	78.60	80.54	70.58	108.42	78.80	52.44	55.41	129.04	50.27
6	43.43	39.18	54.57	91.78	76.76	73.13	104.15	74.88	43.01	60.67	127.47	48.43
7	47.38	40.42	48.72	74.94	72.15	72.61	102.74	73.44	46.13	61.56	142.53	60.40
8	51.19	50.35	50.21	75.82	70.53	71.19	92.50	69.33	47.48	69.76	143.88	56.27
9	55.13	52.68	52.55	67.86	72.35	66.33	95.81	65.69	52.16	71.27	146.34	60.61
10	56.27	54.05	50.71	72.90	71.59	60.09	93.77	68.42	53.11	71.53	154.07	58.83
11	44.30	44.62	45.57	80.29	69.63	59.91	104.34	69.59	45.36	59.70	150.09	53.88
12	56.18	53.19	46.96	69.27	68.26	65.63	89.46	71.55	50.76	70.00	150.23	57.06
13	40.10	45.09	54.64	82.60	75.81	69.70	98.75	78.08	49.37	54.68	142.95	51.93
14	47.15	45.56	56.51	84.92	76.04	77.05	99.65	73.80	50.28	59.82	134.70	52.84
15	50.14	53.14	53.38	81.53	77.93	78.81	102.25	74.24	57.16	68.05	144.02	61.29
16	44.02	33.86	43.87	87.65	64.17	85.40	97.59	70.10	47.05	56.50	130.94	44.52
17	38.30	40.69	52.01	81.73	77.00	76.38	91.41	73.47	48.45	52.55	121.44	45.80
18	52.95	48.97	48.24	74.23	77.22	74.49	88.99	75.38	46.38	61.52	140.24	56.33
19	53.34	55.66	42.20	67.97	67.57	63.48	76.64	57.92	52.90	70.45	154.69	56.27
20	50.94	49.03	44.35	62.87	68.71	62.10	76.61	63.49	52.05	71.43	146.70	54.08
21	50.42	46.79	51.78	75.03	76.95	67.14	91.82	72.94	44.70	59.30	148.24	53.47
22	47.22	45.97	53.28	65.49	72.04	61.95	99.20	66.35	49.08	61.99	160.36	59.15
23	52.55	60.40	44.62	64.97	66.95	66.76	88.09	67.43	49.75	76.07	172.33	63.34
24	53.08	50.47	43.80	70.49	69.77	69.71	94.50	66.77	51.00	63.69	167.51	56.55
25	45.90	39.48	43.52	79.58	63.93	71.78	92.25	66.80	48.59	54.73	145.05	47.12
26	44.67	40.81	40.74	49.81	55.41	58.83	76.74	58.02	40.79	54.78	168.65	60.70
27	46.38	41.57	37.07	62.41	59.70	65.86	80.16	63.11	45.26	58.27	177.41	55.59
28	45.99	41.92	39.65	66.57	64.01	61.66	82.93	64.15	42.60	57.46	168.10	58.20
29	36.36	40.77	43.81	61.30	61.96	53.97	87.32	69.71	48.46	52.25	162.63	59.82
30	54.69	37.79	41.15	76.15	62.19	78.53	83.73	72.65	41.88	61.16	168.15	51.71
31	58.08	61.22	52.54	61.36	56.11	70.06	91.18	73.77	52.47	68.19	177.29	46.04
32	42.27	39.12	40.64	71.12	68.24	65.56	90.51	75.62	44.63	53.89	160.76	51.71
33	36.49	40.94	36.09	64.39	73.26	44.87	103.36	68.36	45.31	35.91	149.53	48.00
34	40.22	42.36	43.55	66.25	57.53	63.38	85.26	73.13	45.53	58.63	143.54	45.80

Figure A-4. Results of Multiple Regression Equations: Factors Explaining the Use of Selected Drug Classes

	Cardio/ Beta blockers	Cardio / calcium channel blockers	Cardio / diuretics	Cardio / renin-angiotensin	Cardio / combos	Cardio / dyslipidemics	Sum of all Cardio drugs	Blood glucose regulators	Respiratory
REGRESSION 1									
R Square	*0.16*	*0.31*	*0.08*	*0.12*	*0.13*	*0.05*	*0.19*	*0.19*	*0.02*
t Stat									
% with hypertension	-0.42	**2.19***	-0.69	-1.06	**2.08***	-0.40	0.14		
% with high cholesterol	**2.33***	1.73	1.63	2.01	-0.32	1.25	**2.38***		
% with diabetes								**2.71****	
% with asthma									-0.87
REGRESSION 2									
R Square	*0.16*	*0.59*	*0.00*	*0.14*	*0.00*	*0.28*	*0.29*	*0.32*	*0.02*
t Stat									
average of risk score	**2.43***	**6.79****	0.00	**2.29***	0.37	**3.55****	**3.63****	**3.85****	0.72
REGRESSION 3									

R Square	*0.23*	*0.59*	*0.10*	*0.26*	*0.17*	*0.42*	*0.34*	*0.32*	*0.03*
t Stat									
% with hypertension	-1.17	0.33	-0.23	**-2.16***	**2.37***	**-2.48***	-1.08		
% with high cholesterol	1.44	0.03	1.81	0.89	0.19	-0.46	1.22		
% with diabetes								0.49	
% with asthma									-0.72
average of risk factor	1.68	**4.57****	-0.80	**2.45***	-1.11	**4.34****	**2.60****	**2.48***	0.54

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Figure A-4, cont.

	Cardio/ Beta blockers	Cardio / calcium channel blockers	Cardio / diuretics	Cardio / renin-angiotensin	Cardio / combos	Cardio / dyslipidemics	Sum of all Cardio drugs	Blood glucose regulators	Respiratory
REGRESSION 4									
R Square	*0.82*	*0.84*	*0.70*	*0.69*	*0.61*	*0.81*	*0.80*	*0.62*	*0.60*
t Stat									
% with hypertension	0.11	-0.67	-0.59	-0.94	0.54	-0.59	-0.20	-1.26	
% with high cholesterol	1.82	0.58	1.57	1.10	0.97	1.57	1.81	1.08	
% with diabetes	-0.35	1.59	-0.13	1.31	0.88	-0.13	0.75	0.90	
% with asthma									0.67
average of risk factor	0.73	1.66	-0.88	0.17	-0.27	-0.88	1.10	1.78	1.53
% Medicare Enrollees Under Age 65	0.69	-0.07	1.71	0.52	-0.73	1.71	-0.07	-0.26	-0.14
% Medicare Enrollees Over Age 85	1.68	0.51	**2.80****	-0.79	-0.68	**2.80****	0.84	-0.08	-0.34
% heavy drinkers	1.23	-1.30	-0.91	-0.80	-1.70	-0.91	-0.69	-1.38	
% reporting good or better health status	0.87	1.03	1.25	0.39	1.16	1.25	1.82	1.19	0.21
% current smokers	0.45	**2.84****	1.86	0.86	0.44	1.86	1.75	1.89	0.78
% of people living in a metropolitan area	-1.19	1.11	0.02	1.12	0.70	0.02	-0.46	-0.33	-0.24
% HS graduate or higher	-0.12	0.18	-0.26	1.81	0.27	-0.26	0.16	-0.59	-0.79
HMO Penetration Rate	-0.41	-0.14	-0.07	0.72	-0.34	-0.07	-0.19	-1.22	0.54
Non-Federal Physicians per 100,000 population	**2.88****	1.96	0.16	1.93	-1.92	0.16	1.91	0.61	**-2.95****
%of drug stores that are independent	-0.92	1.89	-1.22	1.65	1.50	-1.22	-0.04	-0.05	-0.63
Estimated # Licensed Pharmacists per 1,000 people	-0.34	0.24	-0.80	-0.12	0.35	-0.80	-0.52	-0.27	0.19

Figure A-5. Sources for Explanatory Variables Tested

Factor	Source
Percent of the population living in a metropolitan area	U.S. Census Bureau, Census 2000 Summary File 1
Percent with a High School degree or higher	U.S. Census Bureau, 2003 Current Population Survey
% Medicare Enrollees Under Age 65	CMS
% Medicare Enrollees Over Age 85	CMS
HMO Penetration rate	KFF State Health Facts. Taken from the Interstudy Competitive Edge 13.1, Part II: HMO Industry Report.
Percent of the population reporting good or better health status	Center for Chronic Disease Prevention and Health Promotion, Behavioral Risk Factor Surveillance System (BRFSS), 2003
% heavy drinkers	BRFSS, 2003
% with high cholesterol	BRFSS, 2003
% with diabetes (not pregnancy related)	BRFSS, 2003
% with asthma	BRFSS, 2003
% with Hypertension	BRFSS, 2003
% current smokers	BRFSS, 2003
Physicians per 100,000 population	KFF State Health Facts. Taken from American Medical Association, Physicians Professional Data, and Census.
Licensed Pharmacists per 1,000 people	NACDS Chain Pharmacy Industry Profile 2003
Pharmacies per 1,000 population	NORC Computation using NACDS and Census data
Independent pharmacies as a percent of all pharmacies	NACDS Chain Pharmacy Industry Profile 2003
Median annual pharmacists wages	Bureau of Labor Statistics, 2003
Median gross apartment rent	2000 Census: Summary File 3; Table GCT-H9: Financial Housing Characteristics