EVALUATION OF DATABASES FOR 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. 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. The purpose of this project was to assist ASPE in assessing and refining the risk adjustment model under development by CMS. The project was structured around three sets of analyses: to assess databases used in development of the risk adjustment model; to identify and assess sources of information on geographic variation in drug prices; and to assist ASPE in understanding and evaluating the levels of financial risk that drug plans may incur and the incentives that plans may face given the complex bid and payment structure of the MMA.

Underlying the accuracy of any risk adjustment methodology are the data used to make that adjustment. While there are a large number of different data sets that have the potential for providing useful information for drug risk adjustment, there was no data set with the full set of data elements required for the Medicare beneficiary population as a whole. The central purpose of Task 1 was to assist in understanding and assessing the range of potentially useful data sets, as well as in assessing and refining the specification of the risk adjustment model. In addition to requiring that plan payments be adjusted based on beneficiary health status, the legislation also requires the Secretary to examine the need for adjusting payments based on evidence of geographic variation in prices and spending. The purpose of Task 2 was to analyze geographic variation in retail drug prices, pharmacy acquisition prices, and beneficiary spending on prescription drugs. The Medicare drug benefit includes three separate mechanisms to limit the financial risks of prescription drug plans (PDPs)—risk adjustment, reinsurance, and risk corridors. These risk protections are important because Medicare PDPs may face substantial, hard-to-quantify risks. Task 3 examines two aspects of these risk-limiting mechanisms--the MMA language itself and the effectiveness of these factors in limiting plans' financial risks. This includes analyses of how these factors are to be implemented, whether there are any unforeseen interactions among these pieces, and whether opportunities are created for plans to "game the system."

Analyses were conducted using several different sources of data. For Task 1, two primary data sets were used--Blue Cross Blue Shield Federal Employee Program (BCBS FEP) data and linked Medicare-Medicaid data. Both data sets included demographic and diagnostic information and data on prescription drug spending. Task 2 analyses of prices relied primarily on two types of pricing data: retail price data from the IMS Health (IMS) National Prescription Audit™ (NPA™) database, representing an estimated 46 percent of all dispensed retail prescriptions in the United States, and acquisition price data from the IMS Health National Sales Perspectives™ data. Task 2 analyses of spending were based on the

BCBS FEP data. Five years of data from the Medicare Current Beneficiary Survey (MCBS) Cost and Use files were pooled to form the database for use in Task 3.

With respect to assessment of the development of the risk adjustment model, a few key findings emerge. Overall, given serious data limitations, the ultimate model developed and put forward by CMS is quite reasonable and defensible from clinical, statistical, and policy perspectives. From the analyses conducted under this contract, the model does not appear to be adversely affected, as anticipated, by some of the differences between FEP enrollees and the overall Medicare population. Specification of the model with respect to defining the dependent variable as plan-covered spending arose as an important decision and was settled satisfactorily. Ultimately, the most serious problem with the model is related to the lack of a common data set that would allow estimation of the model simultaneously for the full range of covered sub-populations. This applies most importantly to low-income persons and beneficiaries under 65 years of age, but also to institutionalized beneficiaries. Because of these limitations, underlying issues regarding refinement of the functional form, for example, received less attention than was perhaps ideal.

In the analysis of geographic variation of prices, there was little state or regional variation in either retail prices or acquisition prices. Because price variation is minimal, a plan payment adjustment for geographic variation in drug prices may be unnecessary. The greatest variation in retail prices at the state level is for Puerto Rico, Hawaii, and North Dakota. Because Hawaii and Puerto Rico are designated as separate regions, the Department may wish to monitor and explore further whether higher prices in those places may call for adjustments at some point.

By contrast, we found more substantial variation in drug utilization, whether measured by unadjusted FEP spending or after making adjustments to account for the features of the Medicare Part D benefit. Furthermore, the application of risk adjustment does not eliminate the state-level variations in utilization. Analysis of projected Part D premiums, under the assumption that plans' costs will reflect average state spending, shows that enrollees in half the states might face premiums of at least 10 percent above or below the national average. We found some evidence that health status factors are the source of some of this variation, suggesting that there is room for some future improvements to the risk adjustment system. More generally, if geographic variations persist under Medicare Part D, policymakers may want to consider options for ensuring that beneficiaries do not face premium differences solely based on where they live.

In terms of risk-limiting mechanisms, results from the actuarial model indicate that the combined effect of reinsurance, risk adjustment, and risk corridors is quite strong in limiting MMA drug plan profits and losses. Specifically,

- Reinsurance appears to cut the raw profits or losses roughly in half, on average, for most of the populations. Risk adjustment then appears to remove about a third of the remaining profit/loss.

- The risk corridors then cut the remaining profits or losses by roughly two-thirds.

- The net result is that very large original (raw) profits and losses – those that would obtain with no adjustments – are reduced to about one-seventh of their original level after all three risk-limiting rules have been applied.

In terms of unexpected incentives created by the risk-limiting aspects of the MMA, one provision may be worth nothing. Plans may have an incentive to shift their projected costs onto the overhead portion of their bid, rather than onto projected drug spending. This occurs because only the drug spending portion of the bid is counted in the risk corridor calculation. For a given total amount bid, a plan is more likely to show losses under the risk corridors (and so receive additional risk corridor payments) if the bid overstates overhead costs and understates projected drug costs.

EVALUATION OF DATABASES FOR DRUG RISK ADJUSTMENT

TASK 1-- VALIDATION AND REFINEMENT OF RISK ADJUSTMENT MODEL

Introduction

The risk adjustment of payments under the MMA is intended to make financial transactions among beneficiaries, CMS, and vendors of both Prescription Drug Plans (PDPs) and Medicare Advantage (MA) plans more equitable. 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) will be used to establish a national benchmark—created by aggregating across all bids. Beneficiaries' premiums will then be 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 perspective of the Medicare program--in terms of fairly paying plans for the services delivered, allocating funds equitably between beneficiaries in private plans and in traditional Medicare, maintaining appropriate incentives, and establishing beneficiary out-of-pocket costs within 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., by attracting low-cost enrollees).

Risk-adjusted payments to Medicare+Choice plans—required under current law—are being phased in so that 75 percent of the payment will be risk-adjusted in 2006. The risk adjustment methodology has been developed and 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 outpatient and physician data. The new risk adjustment methodology—CMS Hierarchical Condition Category or HCC—is based on beneficiaries' chronic disease diagnoses. The MMA requires that CMS consider this risk adjustment model in developing a corollary model for risk adjusting payments under the drug benefit. While there are many similarities in the underlying methods behind predicting overall health care use and drug use, there are a number of differences that make it critical to invest in development of a model specific to drugs. For example, 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.[1] As a result, the relative importance of diagnostic versus demographic variables may differ.

[1] Hogan C. "Predicting Medicare Beneficiaries' Drug Spending Using Diagnoses from Claims Data," Briefing for DHHS Staff, March 20, 2001.

Similarly, while the risk adjustment methodology used for other health care services comprises distinct sets of weights for community-based and institutionalized beneficiaries,[2] it was not clear at the outset whether this should be the case for the drug risk adjuster.

As a result of these and other issues, there may be ways to improve the predictive power of the model by reexamining whether particular measures should be included and, if so, how they should be included. For example, it is likely to be important to adjust payments for low-income beneficiaries, because of both expected effects on utilization of being low-income and the special subsidies that will be paid for these beneficiaries. Although it is clear that low-income status should be included in the model, it is not clear whether it should be included as a simple dummy variable, resulting in a fixed payment difference due to being low income, or as a dummy variable interacted with the scores of diagnostic indicators, resulting in payments for these beneficiaries that reflect both their low-income status as well as their particular diseases.

Underlying the accuracy of any risk adjustment methodology are the data used to make that adjustment. In developing a risk adjustment methodology for payments for drugs to PDPs and MA plans, data items that were previously not required in risk adjusters are needed. While there are a large number of different data sets that have the potential for providing useful information for drug risk adjustment, there was no data set with the full set of data elements required for the Medicare beneficiary population as a whole.

Ideally, a data set to be used in calculating the risk factors for the new drug benefit would include a number of features. Most basically, there need to be two years of data—the first with individual-level diagnostic information and a subsequent year's worth of data on prescription drug spending. The drug spending data would be most useful if it includes individual records so that one can count number of prescriptions, payment for each drug purchase (including out-of-pocket payment and amount reimbursed), and the drug name (preferably NDC). Person-level demographic information is needed—including age, sex, income (or at least eligibility for the low-income subsidy), and other program eligibility (e.g., Medicaid full or partial status). In terms of coverage, one would want to have represented in the data set the full range of Medicare beneficiaries, including those with different types of coverage and income levels, as well as the institutionalized. In the best of all possible worlds, it would be useful to have independent information on the structure of each individual's drug benefit so as to better understand behavioral responses to changes in coverage parameters.

In the presence of an ideal data set, development of a drug payment risk adjustment model could focus on the two questions stated above – which variables should be included and how should they be included? The ideal data set does not exist, however, which greatly complicates the process of refining and estimating a model. As CMS has worked to develop useable estimates from which a satisfactory model can be implemented, ASPE has been trying to review and assess the options for dealing with the limitations of the available data sets.

[2] There are also weights for frail beneficiaries in special programs and for ESRD beneficiaries.

Each of the data sets considered has strengths and weaknesses with respect to the accuracy, representativeness, and breadth of the data as well as its cost and availability. One of the purposes of Task 1 was to assist in understanding and assessing the range of potentially useful data sets. In addition, project objectives emphasized assessing and refining the specification of the risk adjustment model.

The work described in this report occurred over the period of time in which the risk adjustment model was being developed at CMS. The model went through numerous changes in the course of development and much of NORC's work was conducted using preliminary versions of the model. Thus, while the general implications of the findings are likely to remain the same, the specific results will depend on the final form of the model.

Data Sources

In this section we describe some of the specific features of two data sources that could potentially be used to assess the drug risk adjustment model. The data sets discussed are: the Blue Cross Blue Shield Federal Employee Program (FEP) data and linked Medicaid-Medicare data. The FEP data offered a number of strengths including a large sample size with detailed records as well as immediate availability. It was decided at the outset to attempt to supplement analysis of the FEP data with other data sets and to focus those efforts on obtaining Medicaid or other data that would more accurately represent at least some portion of the low-income Medicare population.

Blue Cross Blue Shield Federal Employee Program (FEP) data

The Federal Employee Program (FEP) of the Blue Cross Blue Shield Association is a nationwide preferred provider organization (PPO) product offered to Federal employees and retirees. FEP has a number of features that make it potentially useful for modeling risk adjustment for prescription drugs. First, FEP covers a large elderly population (about 650,000 retirees, plus spouses, and including institutionalized beneficiaries) with at least some representation from a large number of geographic areas. Second, the combined FEP acute-care claims and pharmacy data provide both drug and diagnosis information. This allows a risk adjustment model to be estimated (at least provisionally) without matching to CMS claims files, a substantial advantage over stand-alone drug claims data.[3] A person-level variable indicating total drug expenditures (person and plan liability) is included in the file.

There are also several limitations to the FEP data. While the population represented is widespread geographically, it is concentrated in the Washington, DC-Baltimore area and it is not clear whether and how the FEP population differs from other Medicare beneficiaries. Perhaps more critically, the FEP data represent only one (quite generous) benefit structure so the ability to draw inferences about the relationship between health status and drug use may be seriously limited. In addition, the standard FEP files obtained by CMS for the risk adjustment work do not show drug prices due to contractual obligations with the PBM. The

[3] Diagnoses are available because FEP serves as secondary insurer for Medicare-covered retirees. Medicare-covered services with coinsurance or deductible liabilities generate FEP secondary insurer claims. These claims account for about half of all physician claims in the FEP files.)

standard claims show national drug code, date of prescription, and other indicators (generic, formulary), but no charge or cost information at the individual drug level.

Linked Medicare-Medicaid Data

It was decided at the outset to attempt to supplement analysis of the FEP data with other data sets and to focus those efforts on obtaining Medicaid or other data that would more accurately represent at least some portion of the low-income Medicare population. Initial efforts focused on investigating the value of conducting some analyses using stand-alone Medicaid data (i.e., not linked to Medicare claims data). In order to be of value as a stand-alone data set, however, the Medicaid data must fully capture acute care diagnoses necessary for use in the risk adjustment model. After discussions with researchers who had worked on the Multistate Database for Dual Eligibles as well as representatives from the Research Data Assistance Center (ResDAC) who are familiar with Medicaid data, NORC project staff were convinced that Medicaid data alone were not likely to provide a complete diagnostic profile for dual eligibles. This is due to the fact that, where Medicare is the primary payer, the Medicaid record may show only the Medicaid co-pay and does not always include diagnostic data.

Thus, it was decided to pursue linked Medicaid-Medicare data. Because the merging of Medicaid and Medicare data through the CMS data center was expected to take some time, NORC explored other existing sources of linked data and identified such data for calendar years 2000 and 2001, available from Jen Associates. These data were purchased for use in this project, after finalizing the specification of the data files and variables needed and gaining letters of support in order to gain access to the data.

The database obtained represents a 5 percent national sample, covering the elderly who were eligible for Medicare in 1999 and who were also eligible for Medicaid in 2000. The file was created beginning with a 1999 national 5 percent sample of Medicare beneficiaries. These were matched to the 2000 national Medicaid Statistical Information System (MSIS) data. Records for persons in HMOs, those with a third-party payer and those without complete drug coverage (e.g., QMBs, SLMBs) were deleted. The file includes persons less than 65 years of age as well as those 65 and over, and persons residing in institutions.

Variables on the file include administrative data (recipient ID; recipient demographics, including state of residence; monthly administrative status for Medicaid in 2000 and Medicare enrollment for 1999 ; and a monthly flag identifying persons with a long-term nursing home stay in 1999); 1999 diagnostic data (one record per Medicare primary and secondary diagnosis--primarily from hospital and physician claims); and prescription drug data for 2000 (single record per Medicaid drug claim including NDC and charge/payment). There are approximately 163,665 person-level records for analysis.

Availability of Other Data Sources

At the outset of the project, the availability of other data sources for use in refining and testing the model was reviewed and considered. Some of the data sources discussed include TRICARE data (from the Military Health System), private plan data, and pharmaceutical assistance program data. It was decided that acquisition and exploration of

the Medicaid data should take highest priority because of the importance of accurately accounting for the low-income population's use of prescription drugs. Ultimately, there was not sufficient time to involve other data. Any additional efforts aimed at identifying alternative data sources with which to further test the model should emphasize populations with different and less generous benefit packages than the FEP benefit structure.

Results: Validation and Refinement of the Model using FEP BCBS Data

In this section, we describe a series of analyses related to the risk adjustment model being developed by CMS. The purpose of these analyses was to assess a number of different aspects of the specification of the risk adjustment model and its applicability to different Medicare sub-populations. Specifically, the following analyses were undertaken:

- Comparison of FEP enrollees by diagnosis to the overall Medicare population;
- Assessment of geographic representation of FEP enrollee population relative to the Medicare population;
- Comparison of the rate of institutionalization among FEP enrollees and the overall Medicare population; and
- Comparison of alternative calculations of the dependent variable in the risk adjustment model.

This information was to be used by ASPE in working with CMS to ensure that the risk adjustment model put forward would meet the Department's goals in terms of paying plans fairly given the health status of their enrolled population and providing appropriate incentives for enrollment of all Medicare beneficiary sub-populations.

As described below, results of the analyses indicated that differences between the FEP population and the overall Medicare population with respect to the distribution of diagnostic conditions and in terms of geographic distribution are unlikely to have a significant impact on the results of the model. The rate of institutionalization among FEP enrollees was found to be substantially lower than for the Medicare population overall, and the ratio of predicted to actual spending for permanent nursing home residents is greater than one, indicating that the model over-predicts spending for this group. However, since dual eligibles constitute a substantially greater proportion of the institutionalized population than do the privately insured, it is important to examine spending patterns for the Medicaid institutionalized before drawing conclusions about any adjustments made to the risk adjustment model when determining payments. Several approaches to modeling of the dependent variable for the risk adjustment model were explored. While neither total spending nor plan-covered spending were uniformly able to predict spending well among all segments of the Medicare population, it was concluded that the plan-liability approach will be more sensitive to variation among groups under potential alternative benefit structures.. Each of these analyses is discussed in more detail below.

Comparison of FEP Enrollees by Diagnosis to the Overall Medicare Population

The risk adjustment model relies primarily on using diagnoses recorded in the claims records to predict prescription drug expenditures. Thus, understanding how the distribution of diagnoses compares between FEP BCBS enrollees and the entire Medicare population is essential to understanding how helpful FEP BCBS data will prove to be in the development and refinement of the risk adjustment model. To compare the distribution of diagnoses across the two populations, we obtained data on the overall Medicare population from the CMS website; these data were based on a 5 percent sample of fee-for-service beneficiaries alive in January 2000 and who had 12 months of Part A and Part B experience in the data collection year (1999). The number of DGs used in the analysis was limited to those available on the CMS website; 27 DGs from the model were collapsed into 12 more aggregated groupings so as to correspond to available estimates. Using the 1999 FEP BCBS data, we then tabulated the proportion of the aged enrollee population with each of the diagnoses. For the vast majority of disease groups, the proportions between the two populations differed by less than one percent. To account for the differential weight placed on different disease groups by the model, we multiplied the difference in each disease's prevalence in the two populations by its estimated coefficient in the risk adjustment model. These impacts were also minimal, indicating that there is not a particularly large difference in the distribution of diseases with large effects on spending. The conclusion from this analysis was that any differences in the distribution of disease across the Medicare and FEP populations were unlikely to have a significant impact on the results of the model.

Assessment of Geographic Representation of FEP Data and Impact on the Model

Another concern was that the concentration of FEP enrollees in the Washington DC area and eastern U.S. would undermine its relevance to understanding the national Medicare population. Thus, we analyzed the effect on the model of weighting the FEP data to better match the actual geographic distribution of the total Medicare beneficiary population. We first calculated the number of aged Medicare enrollees for each county. (In some cases, the number of aged enrollees was missing and the total number of enrollees--aged and disabled--was substituted.) The data available on CMS' website were current as of July 2003. We then calculated the number of FEP enrollees by county, using the 2002 data. Geographic weights were constructed, equal to the number of Medicare enrollees divided by the number of FEP enrollees in the same county. The one exception was Alaska where, because of problems with the state (SSA) code, we combined Alaska boroughs into one county and calculated a state-level geographic weight for Alaska residents. After re-weighting the FEP data with these constructed geographic weights, we compared the resulting coefficients from the risk adjustment model. In order to assess the importance of any changes in the coefficients, we ranked the coefficients by size before and after the re-weighting and compared. In the table below, we list all of the measures with coefficient estimates that changed by more than ten relative positions. So, for example, the coefficient on Other Eye Disorders in the initial model was the 59th largest of the 113 disease coefficients in the model, but became the 17th largest in the geographically re-weighted model. These results suggest that there may be significant geographic variation in the cost of these conditions, but because these 8 conditions (out of 113) are small (only one represents 0.5 percent of FEP enrollees and most are considerably smaller), we consider the geographic re-weighting to have a negligible effect

on the model. As a percent of a total diagnoses represented in the model, these conditions represent an even smaller proportion.[4]

Figure 1. Measures With Coefficient Estimates That Change More Than 10 Relative Positions Between Initial and Geographically Re-weighted Models

		Coefficient Rank			
Condition	**Label**	**Initial model**	**After Geographic Re-weighting**	**% FEP enrollees with condition**	**% of total diagnoses**
CC124	Other Eye Disorders	59	17	0.03	0.00
CC132	Nephritis	92	64	0.55	0.09
CC159	Major Fracture, Except of Skull, Vertebrae, or Hip	47	32	0.29	0.05
CC17	Diabetes with Acute Complications	96	65	0.34	0.05
CC26	Cirrhosis of Liver	115	100	0.30	0.05
CC48	Delirium and Encephalopathy	52	35	0.20	0.03
CC57	Personality Disorders	74	62	0.11	0.02
CC70	Muscular Dystrophy	58	18	0.02	0.00

Notes: Based on estimates from risk-adjustment model that includes 113 clinical conditions and 16 demographic categories (7 age groups * sex; originally eligible through disability * sex). Nearly two-thirds of the clinical conditions and all demographic measures included in the model are present in over 1.00% of enrollees. Final column (% of total diagnoses) represents the number of diagnoses for each of the 8 CCs among all FEP enrollees in 2001/2002 divided by the number of diagnoses among all FEP enrollees across all CCs included in the model in 2001/2002.

Examination of Impact of Institutionalization on the Risk Adjustment Model

The purpose of this sub-task was to calculate the rate of institutionalization in the FEP enrollee population and assess the effect of institutionalization on actual and predicted expenditures. Because the FEP data did not initially include an indicator identifying institutionalized enrollees, we obtained the Minimum Data Set (MDS) files for the years 1999, 2000, and 2001 from CMS and linked these data to the FEP data by person ID. The MDS data include information on services provided in a nursing home and thus allow establishment of periods of residence in an institution. A flag was created to identify permanent nursing home residents; they were defined as someone who was in a nursing home but was never discharged to home (with or without home health), board and care/assisted living, or a rehabilitation hospital. For persons who died during the period, expenditures were weighted according to the number of months they were in the data set. This flag was then used to assess the impact of institutionalization on drug expenditures; the indicator was also sent to CMS for their use in developing the adjustment for institutionalized beneficiaries.

Once the indicator was constructed, the percent of FEP enrollees flagged as permanent nursing home residents was calculated in order to compare it to published sources on the

[4] Final column (% of total diagnoses) represents the number of diagnoses for each of the 8 CCs among all FEP enrollees in 2001/2002 divided by the number of diagnoses among all FEP enrollees across all CCs included in the model in 2001/2002.

institutionalized rate for the overall Medicare population; this latter rate was found to be approximately 5 to 6 percent.[5]

Figure 2 provides the number of persons flagged as permanent nursing home residents, the percent of nursing home residents who are considered 'permanent' residents, and the percent among all FEP enrollees for each of the 3 years. These results indicate that the rate of institutionalization among FEP enrollees is markedly lower than among the Medicare population overall, raising concerns about how well a model based on the FEP data will account for this subpopulation.

Figure 2. Institutionalized Beneficiaries as Percent of FEP enrollees

FEP Population	1999	2000	2001
# flagged as permanent nursing home resident	17,034	17,406	18,814
% among those in NH (from MDS file)	48.50%	48.53%	51.59%
% among all FEP enrollees	1.75%	1.79%	1.97%

Source: NORC tabulations of MDS and BCBS data, 1999-2001.

This difference in the share of the population that resides in nursing homes is important only if there is evidence that nursing home residence is associated with different drug costs, or, more subtly, if the relationships among diagnoses and demographic characteristics differ for those in nursing homes. The next step, therefore, was to calculate actual drug spending for permanent nursing home residents and compare that spending to the non-institutionalized. Figure 3 provides these comparisons for each of the 3 years. Actual drug spending is substantially higher for permanent nursing home residents than for other FEP enrollees, ranging from 27 percent higher in 2000 to 32 percent higher in 2002.

Figure 3. Drug Spending for Institutionalized and Non-institutionalized FEP Enrollees

Drug spending, unadjusted	2000	2001	2002
PNH (permanent nursing home resident)	$1869	$2181	$2365
Other FEP enrollees	$1473	$1681	$1787

Source: NORC tabulations of MDS and BCBS data, 1999-2001.

We then used the coefficients from the then-current version of the CMS risk adjustment model on the combined populations of institutionalized and non-institutionalized enrollees. These results are presented below In Figure 4. The ratio of predicted to actual spending for permanent nursing home residents is 1.13, indicating that the model over-predicts spending

[5] Information from the Medicare Current Beneficiary Survey (MCBS) indicates that approximately 6 percent of all beneficiaries are "living in long-term care." This represents about 2 million aged beneficiaries.

for this group. However, since dual eligibles constitute a substantially greater proportion of the institutionalized population than do the privately insured, it is important to examine spending patterns for the Medicaid institutionalized before drawing conclusions about any adjustments made to the risk adjustment model when determining payments.

Figure 4. Predicted and Actual Plan-Covered Spending for Permanent Nursing Residents and Other FEP Enrollees, 1999-2001

	Predicted plan-covered drug spending (normed)	Actual plan-covered drug spending (normed)	Ratio of Predicted to Actual
PNH	1.21	1.07	1.13
Other FEP enrollees	1.00	1.00	1.00

Note: Estimates are weighted; model based on total spending.
Source: NORC tabulations of MDS and BCBS data, 1999-2001.

Comparison of Alternative Calculation of the Dependent Variable

The underlying purpose of the risk adjustment model is to explain drug spending based on the health status and demographic characteristics of the enrollee population. However, there are two approaches to defining drug spending (the dependent variable in the model)—(i) total drug spending and (ii) covered (reimbursed) drug spending. The initial modeling approach adopted by CMS relied on the former--using total person-level drug spending as the dependent variable. Since the purpose is to risk adjust plan payments (rather than total beneficiary spending), it was decided that this may not be the appropriate approach or, at a minimum, may lead to a different risk adjustment mechanism. The purpose of this step was to use both approaches and compare the results.

Using the FEP data, we first ran the risk adjustment model using CMS' initial approach, as follows:

1. Use person-level total drug spending as the dependent variable in risk adjustment model.
2. Use coefficients to get predicted total spending from risk adjustment model.
3. At person level, use Part D benefit structure to calculate (predicted) plan-covered spending (net of reinsurance).

We then used the alternate approach, with the following steps:

1. At person level, use Part D benefit structure to calculate plan-covered spending (net of reinsurance).
2. Use calculated plan-covered spending per beneficiary as dependent variable in risk adjustment model.
3. Use coefficients from model in step 2 to predict plan-covered spending.

We then wanted to compare the ratio of predicted plan-covered spending to actual spending, from each of the two approaches. To maintain budget-neutrality, person-level spending was normed to the population mean under each measure.[6] We used pooled 2001-2002 data for this analysis.

Comparing these ratios (predicted to actual spending) across states, demographic groups, and diagnostic categories, we found the following:

- Across states, the predictive ratios using the total spending approach produce ratios that range from 0.92 to 1.15. Using the plan liability approach, the range is approximately the same, 0.92 to 1.16. For a given state, the ratios are quite similar—they differ by no more than 2% and in the vast majority of cases are equal.

- For 7 selected diagnostic categories, the total spending predictive ratios range from 0.88 (HIV/AIDS) to 1.06 (MS). For the demographic groups, the range is more compressed, from 0.96 (men, 95+) to 1.03 (women, 65-69). "Originally disabled males" (those who enter Medicare as disabled and then age into the program) have a ratio of 1.06. The plan liability predictive ratios are equal to 1 by definition (because they are directly entered into the model).

These two approaches provide somewhat different results in terms of payment to plans, but much less variation than was anticipated. In fact, results differed not at all or by a very small amount for 3 of the 7 diagnosis groups and for almost half of the demographic groups. This is likely due to the Part D benefit structure which includes a substantial amount of spending in the 'doughnut' hole, as well as significant reinsurance. These features serve to lessen the variation in plan liability substantially (as compared to the variation in total spending).

A number of other data exercises were conducted to further explore the differences between the two approaches.[7] One general conclusion drawn was that using plan-covered spending worked slightly better in capturing the effects of the Part D benefit structure, but that neither approach worked well at the extremes of the distribution. To the extent that the choice of dependent/outcome measure modeled mattered less than anticipated, it seems that the 'best' modeling approach may be highly dependent on the specific benefit structure. The complex structure of the Part D benefit--where the benefit changes at different spending levels—appears to be partially responsible for this loose correspondence. With future benefits packages that are structured differently, there may be a more decided difference in the two approaches and it is likely that the plan-liability approach will be more sensitive to variation among groups.

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[6] We divided each person's risk score by the mean risk score for the entire population (i.e., we divide predicted and actual plan-covered spending for an individual by the respective mean for all beneficiaries).

[7] We then sorted beneficiaries into deciles based on predicted spending (this was done to duplicate and assess some results produced at CMS and shared with ASPE/NORC). The CMS results from simulating these two approaches (modeling total spending vs. plan-covered spending) result in predictive ratios ranging from 0.87 to 1.3 for the former approach and from 0.92 to 1.66 for the latter approach). [When we replicate the CMS approach, our predictive ratios have a slightly wider range for the CMS model (0.84 – 1.3) and a slightly narrower range for the NORC model (0.93 – 1.5).]

Alternative Modeling Approaches. Two additional approaches were suggested by the NORC team to use in refining the modeling of the benefit structure. The first was to separately model each portion of the benefit structure—the deductible, the range from $250 to $2250 where patient coinsurance is 25%; the 'doughnut' hole from $2250 to $5100 where there is no plan reimbursement, and above $5100 where coinsurance is 5% and re-insurance kicks in. It was decided that this modeling of a four-part benefit structure was too cumbersome and would be politically unacceptable because of the difficulties involved in explaining the process to plans interested in bidding.

The second approach considered was to use a smearing estimator. The smearing estimator provides a way of taking a regression and generating accurate predicted values for some nonlinear transformation of the variable for which the regression was estimated. A common example of such a transformation is a regression estimated in logs, where predicted values are then generated in natural units (anti-logged). When a nonlinear transformation is used, generating unbiased predicted values involves more than just taking the predicted value from the regression and applying the nonlinear transform. In the case of logs, a simple formula is available to account for the effects of the nonlinear transformation, involving both the predicted value and the variance of the error term. Here, however, the nonlinear transformation is the relationship between total drug spending and plan liability created by the Part D benefit structure. In this case, there is no simple formula to generate the correct predicted plan spending from a regression estimated on total spending. The smearing estimator provides a way to obtain unbiased estimates even when no formula exists to account for the effects of the nonlinear transformation of the dependent variable.

The smearing estimator is non-parametric. It does not assume any particular functional form for the distribution of the regression errors or the nonlinear transformation, but instead derives the relationship purely empirically from the data. It works by dividing the data into a large number of segments (e.g., centiles of the dependent variable) and, in each segment, determining the average relationship between predicted total spending and average actual plan liability. Together, these (e.g., 100) data points draw the curve linking predicted total spending to predicted plan liability. Specifically--using FEP data from 2001 and 2002 and inflating expenditures to 2006 dollars (assuming a 7 percent annual inflation rate in drug expenditure)--the following steps were involved:

1. Predicted total drug spending was partitioned into centiles (e.g., 100 small segments).
2. For each such segment, we identified all persons whose predicted total spending fell into that segment.
3. For each such person, actual plan liability was calculated (based on their actual total spending).
4. For all the persons in a given segment, the mean of actual plan liabilities was calculated;
5. Mean predicted total spending was calculated for all persons in a segment.

The final result was a pair of points in each small segment: average predicted total spending and average actual plan liability. This set of points, across all the 100 segments, is the curve used to transform predicted total spending to predicted plan spending. For each centile, we

used the ratio of mean actual plan liability to mean predicted total expenditure as an adjuster. The predicted plan liability for any person is, then, the predicted total spending for that person times the adjuster for the centile that person falls into.

Predictive ratios were generated for a number of demographic and diagnostic groups. A predictive ratio equal to one indicates that spending is perfectly predicted by the model. The predictive ratios generated from the smearing estimator were not substantially closer to one than those generated from the original risk adjustment model. In comparing the CMS model-based predictive ratio to the smearing estimator predictive ratio, we found that those from the CMS model tended to be closer to a value of one for the diagnostic groupings, while those from the smearing estimator were closer to a value of one more often for demographic groups.

Results: Validation and Refinement of Model using Medicaid Data

The purpose of this portion of the analysis was to assess how the risk model predicted spending for persons eligible for both Medicaid and Medicare. As with the analyses of the FEP data described above, our purpose was to assist ASPE in working with CMS to ensure that the risk adjustment model put forward would meet the Department's goals in terms of paying plans fairly given the health status of their enrolled population and providing appropriate incentives for enrollment of all Medicare beneficiary sub-populations. In particular, there was concern that—because the risk adjustment model was developed using data for a well-insured, presumably higher income group—it would not serve the needs of lower-income populations. This might be true if the relationship between patterns of illness (diagnoses) and spending on prescription drugs differed substantially for low-income persons.

In this section, we begin by describing initial analyses examining Medicaid prices, we then present descriptive statistics on drug expenditures by Medicaid enrollees, and finally present information on how the risk adjustment model predicts for the dual eligible population. The analysis of Medicaid prices showed a fair degree of geographic variation in prices underlying measured spending. While use of a standard set of prices would minimize the potential for bias, introduction of standardized prices was not possible within the project timeframe. Descriptive statistics on drug expenditures by Medicaid enrollees indicate that those less than 65 years of age have higher raw drug spending than those 65 years of age and over, and that the institutionalized spend more than community-dwelling beneficiaries. Overall, it appears that the risk adjustment model would result in overpayment for Medicaid beneficiaries, but this masks very different results for different subgroups.

Pricing Analysis

Prior to beginning analysis on the Medicaid data, one of the issues faced was the interpretation of price variables. Because the Medicaid program varies by state and states may negotiate different prices for a given drug, prices in the Medicaid data may differ across states. Based on concern about whether there was systematic price variation by state that would affect model estimation, we conducted some basic analysis of prices across states for the 10 most common NDCs. The results of the most basic analysis are shown in Figure 5. From this preliminary analysis, it seems that prices are relatively clustered.

Figure 5. Ten most commonly-used drugs, percent of prices within given range

Drug	Number of states	Range of mean amt paid	Percent of claims
1	45	$56-69	93%
2	44	$15-22	84%
3	46	$65-82	88%
4	42	$37-44	76%
5	37	$7-10	66%
6	43	$50-61	91%
7	41	$4-7	68%
8	47	$96-113	84%
9	47	$60-74	95%
10	47	$103-122	95%

In order to assess whether there is *systematic* variation, we constructed a Medicaid state price index. The following steps were taken:

1. For each NDC, we calculated the total amount paid by Medicaid and selected the top 50 NDCs that were reimbursed by Medicaid in all states in 2000 and would be reimbursable under Part D;

2. For each of these 50 drugs, we calculated a national spending weight by taking the ratio of total Medicaid amount paid on the drug over the total Medicaid amount paid on all 50 drugs;

3. For each of the 50 drugs, we calculated the average price (payment) over all claims with the NDC code in each state and across the nation;

4. In each state and for the nation as a whole, we calculated a weighted 50-drug price index by taking the weighted (weight calculated in step 2) sum of the average price of each of the 50 drugs;

5. We then calculated the ratio of the state price index over the national price index to get a normed price index for each state.

The resulting state-specific price indices ranged from 0.80 to 1.17,[8] which is fairly typical of national regional indices of this type. The geographic adjustment factor for a typical service under the Medicare Fee Schedule, for example, ranges from about 0.83 to 1.24. For the purpose of using Medicaid data to estimate a risk adjustment model for drug spending, it suggests that there is a fair degree of geographic variation in prices underlying measured spending. To the extent that there is also geographic variation in the distribution of diagnoses used in the model, then there is a risk that the model estimated on the Medicaid population will confound marginal disease cost effects with price differences. Similarly, estimates of risk adjusted spending based on coefficients estimated on another population,

[8] South Carolina was the exception with an index of 1.59.

such as those in the FEP BCBS plan, will be distorted by price differences underlying the spending in each population. While, ideally, a standard set of prices could be used along with reported quantities of drugs from each population to remove this problem, this was not possible within the project timeframe.

Descriptive Statistics

The next step was to produce some simple descriptive statistics on the linked Medicaid-Medicare data to see how unadjusted prescription drug spending in the dual eligible population differed from that in the FEP population on which the model was constructed. As shown in Figure 6, these estimates indicate that actual mean drug spending for dual eligibles in 2000 was approximately $2,329. These estimates of raw spending indicate that the dual eligible disabled population (those less than 65 years of age) spends substantially more than the dual eligible aged population, and those residing in institutions spend more than those dwelling in the community. Overall, dual eligibles living in institutions spend approximately 28 percent more than those residing in the community. This difference varies by age, with the largest gaps found in the two youngest groups. Spending for those living in the community varied by age with the highest spending in the 45-to-54 and 55-to-64 age groups.

Figure 6. Mean annualized dollars paid by Medicaid, 2000

	No. of observations	Mean actual total Expenditure
All	149,306	2,329
Community residents	124,316	2,293
NH residents	24,990	2,496
0-34	8,669	2,270
Community residents	8,403	2,199
NH residents	266	4,395
35-44	15,693	3,163
Community residents	14,868	3,101
NH residents	825	4,213
45-54	15,098	3,205
Community residents	13,964	3,145
NH residents	1,134	3,907
55-64	14,814	2,860
Community residents	13,478	2,767
NH residents	1,336	3,742
65+	95,032	1,975
Community residents	73,603	1,893
NH residents	21,429	2,248

Note: Data are annualized. Three states, Alaska, Hawaii and Tennessee were excluded due to data irregularities. Excludes all persons who had at least one quarter without drug coverage, or at least one month of HMO enrollment, or at least one month of third-party coverage, or at least one month of restricted benefits. NH resident is defined as those in a nursing home in the middle of 2000 (month 6) and had been there for at least three months.

Application of the Model to the Dual Eligible Population

In order to assess how well the CMS risk adjustment model as constructed from FEP data would predict plan-covered drug spending for dual eligibles, we used the coefficients generated from the CMS risk adjustment model run on the FEP data to predict drug spending for beneficiaries covered by Medicaid. The specific steps are detailed here--

1. Run CMS risk adjustment model on FEP data (using 2000 data)
2. Divide coefficients by mean of total drug expenditures (FEP) for purposes of norming.
3. Apply 'normed' coefficients from Step 2 to the clinical conditions and demographics of the Medicaid data and get predicted 'normed' total expenditure for each person
4. Multiply each person's predicted 'normed' drug expenditure by mean of total drug expenditures (Medicaid) to get predicted total expenditure

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At this point, there are two alternate approaches to assessing how well the model works, both based on comparing the predicted amount from the model to the beneficiary's actual drug spending. If the effects of individual diagnoses and demographic characteristics are the same regardless of Medicaid status, then the difference, if any, in spending between Medicaid and other beneficiaries would best be modeled as an additive amount, or intercept shift in the model for these beneficiaries. If, however, the relationship between spending and diagnoses and demographics differs for this subpopulation, then the difference between predicted and actual spending is better captured through a multiplicative relationship, reflecting different slopes in the model. As a result, we examine both the *difference* between actual and predicted values as well as the *ratio* of actual to predicted values. (Note that in this analysis, the reported residual is actual minus predicted and the ratio is actual over predicted whereas in previous sections of this report we have reported the inverse, or ratios of predicted to actual spending.)

Figure 7. Results from applying risk adjustment model to linked Medicare-Medicaid data: Mean residual and mean multiplier by subgroup for dual eligibles.

	N	Mean predicted total expenditure	Mean residual (actual minus predicted)	Mean multiplier (ratio of actual to predicted)
All	161,831	2,590	-268	0.905
Community residents	135,680	2,506	-220	0.896
NH residents	26,151	3,022	-512	0.951
0-34	9,488	1,773	553	1.367
Community residents	9,210	1,747	516	1.344
NH residents	278	2,633	1,734	2.120
35-44	15,939	2,121	1,099	0.849
Community residents	15,092	2,108	1,051	0.779
NH residents	847	2,339	1,930	2.054
45-54	15,364	2,427	797	1.414
Community residents	14,194	2,411	758	1.398
NH residents	1,170	2,619	1,255	1.599
55-64	15,164	2,707	179	1.174
Community residents	13,786	2,670	123	1.150
NH residents	1,378	3,058	710	1.406
65+	105,876	2,741	-766	0.760
Community residents	83,398	2,651	-756	0.740
NH residents	22,478	3,072	-805	0.831

Note: Data are annualized, linked Medicare-Medicaid data. Alaska, Hawaii and Tennessee were excluded due to data irregularities. Excludes all persons who had at least one quarter without drug coverage, or at least one month of HMO enrollment, or at least one month of third-party coverage, or at least one month of restricted benefits. NH resident is defined as those in a nursing home in the middle of 2000 (month 6) and had been there for at least three months This

version also includes drugs paid for under Part B as well as drugs that are specifically excluded from reimbursement under Part D. Since we were unable to exclude them from the FEP model (because of lack of drug-level price data), we did not exclude them here.

Overall, it appears that the model would result in overpayment for Medicaid beneficiaries ($268 as a single adjustment or about 10% as a percentage adjustment), but this masks very different results for different subgroups. This overall effect is the result of overpayment for Medicaid beneficiaries aged 65 and over; for all under-65 age groups, the model results in fairly large underpayment. For example, for those in the 45-to-54 age group there would be a $797 underpayment (or roughly 40 percent, from multiplicative model) for Medicaid beneficiaries, compared with the $766 overpayment (or roughly 24 percent for multiplicative model) for those over 65. This is due, at least in part, to the absence of age dummies for those under 65 in the CMS risk adjustment model. Because these beneficiaries spend more on drugs, controlling for diagnoses, than those over 65, this results in a systematic underpayment.

Similarly, there appears to be a systematic difference for those Medicaid beneficiaries who live in nursing homes. Overall and among those over 65, risk-adjusted payments would be systematically too high, while for those under 65, there would be very high levels of underpayment for nursing home residents, with plans receiving only about 60 percent of actual spending for nursing home residents under 35.[9]

The difference between the implicit adjustment called for by the additive versus multiplicative approaches is of concern and suggests that this is an area that warrants additional analysis. Ultimately, robust estimates that will deal effectively with this problem require availability of a data resource that includes Medicaid and non-Mediciad beneficiaries across both nursing home and community residents and both over-65 and under-65 age groups. With such a data resource, the importance of the functional form used to incorporate Medicaid, nursing home, and under-65 status can be more carefully studied.

Merging Medicaid and FEP Data

In order to produce a final set of risk adjusters, it was necessary for CMS to combine the FEP data with the linked Medicaid-Medicare data. This combined data set would then permit different sub-populations of the Medicare beneficiary population to be examined using standardized assumptions. To accomplish this objective, Medicaid spending was essentially 're-scaled' to the level of spending in FEP data, using the following steps:

1. The risk adjustment model was estimated on BCBS data, using only the elderly (65+), non-institutionalized population.
2. The coefficients from that model were used to get predicted expenditures for the Medicaid elderly, non-institutionalized population.
3. The ratio of predicted Medicaid spending to actual Medicaid spending was calculated.
4. This ratio was used to scale the Medicaid data to the BCBS data.

[9] We arrive at the 40% figure by summing the mean predicted total expenditure of $2633 and the residual of $1734 and then calculating $1734 as a proportion of that sum.

5. The data in the combined data set were weighted to make the data representative of the Medicare population.

In Figure 8, we present predicted and actual plan liability, comparing community dwelling and institutionalized beneficiaries. The estimates in this table used 2002 FEP data and 2000 Medicaid data with expenditures inflated to 2006 level by using a set of annual inflation rates projected by CMS' Office of the Actuary (OACT).[10] In addition, spending was adjusted for the community-dwelling population to account for differences in spending predicted to result from differences between the FEP benefit structure and the Part D benefit. This adjustment was also based on work done by OACT.

Figure 8. Predicted and actual plan liability for community and institutionalized beneficiaries, less than 65 vs. 65 and older

	No. of persons	Mean actual plan liability	Predictive Ratio
Medicaid, community			
<65	51,083	1,138	1.0
65+	74,363	984	1.016
Medicaid, institutionalized			
<65	3,592	1,610	0.815
65+	21,607	1,193	0.919
All institutionalized			
<65	3,592	1,610	0.815
65+	33,770	1,193	0.943

These results show predictive ratios (predicted to actual spending) by age and institutional status; the "All" category includes FEP enrollees as well as Medicaid enrollees for the 65+ population but the less-than-65 population is exclusively Medicaid as the FEP data do not include persons in that age group. The results indicate that the model under-predicts for the less-than-65 population and for the institutionalized population. Recalling that earlier results showed over-payment for the institutionalized (based on FEP enrollees only), here we see that the overall effect when combining the two populations is under-payment for institutionalized persons. Combining FEP and Medicaid enrollees in this regard lowers the extent of underpayment but only modestly.

Summary: Adjustments for the Low-income Subsidy, Induced Demand, and Institutionalized Beneficiaries

As the risk adjustment model was being developed at CMS, part of NORC's role was to act as an agent for ASPE in working with CMS staff. In this capacity, NORC staff in some instances served as a liaison with CMS researchers, gathered information on ongoing developments at CMS, conveyed and interpreted these activities to ASPE staff, and monitored work being conducted at CMS. In this section of the report, we provide a general

[10] These estimates were based on the newer version of the model (received from CMS on Jan. 21, 2005).

overview of these activities, focusing on adjustments made to the model including those to account for the impact of the low-income subsidy; induced demand effects from a change in benefit structure; and differences in spending by institutionalized beneficiaries.

Adjusting for the Standard Part D Benefit

In the initial stages of development of the risk adjustment model, the model coefficients were estimated based on the cost-sharing patterns of the FEP BCBS benefit, which is considered to be a more generous benefit than the standard Part D benefit that will be faced by the Medicare population not receiving a low-income subsidy. Because the beneficiary cost sharing is somewhat higher under Part D than in the FEP BCBS benefit, observed spending in the data set was reduced to reflect lower expected spending from the higher cost sharing. The amount of the reduction was based on an "induced demand effect" estimated by CMS actuaries using data from the Medicare Current Beneficiary Survey (MCBS). The change in spending that would result from an individual moving from the FEP benefit to the Part D benefit was estimated to be 19.4 percent; in other words, total spending was decreased for all observations in the data set by this amount to account for higher cost-sharing requirements. At this stage in the development of the model, institutionalized beneficiaries were not part of the database and, therefore, their spending was not adjusted.

Adjustment for Institutionalized Beneficiaries

Analyses of actual and predicted total spending and plan liability for institutionalized beneficiaries were conducted, as reported above, using both the FEP and the linked Medicaid-Medicare data. In the case of the former group, it was found that the model overpaid for permanent nursing home residents while in the latter the model underpaid. In both cases, actual spending was higher among the disabled than for the elderly population. In combining these analyses in order to implement an overall adjustment for the institutionalized population, CMS derived an adjustment or long term care multiplier of 1.08 for Medicare beneficiaries 65 and over residing in a long term care institution and 1.21 for Medicare disabled enrollees residing in an institution. For individuals who are institutionalized, no low-income adjustment (described below) is applied.

Standardizing Prices across Different Payers

An additional adjustment made by CMS was for differences in pricing by payer. CMS assumed that in order to standardize to full retail levels, prices for Medicaid enrollees had to be increased by 19.5 percent and for persons covered under employer-sponsored plans by 15 percent. In response to this, the NORC team did a quick analysis of MCBS drug prices by payer. Price indices were constructed where the pricing unit was the drug name plus the size of the prescription (number of tablets). For non-tablet drugs (e.g, inhalers), this analysis assumes that all prescriptions had the same number of units. For tablet-type drugs, it was assumed that all pills were the same size for a given drug. The price indices were calculated based on the total amount paid by all sources, classifying payer by the beneficiaries' main type of drug coverage. The price index reflects the prescription mix of each payer (a Paasche index), and the reference price is the average of all payers. This was done for all drugs on the file and for the top 50 drug/unit combinations. Results indicate that Medicaid rates are only slightly below average (index of 0.98), and that private employer-

sponsored plans pay somewhat more than average (1.09). While this analysis should not be considered definitive, at least for the employer-sponsored-plan adjustment, it does not offer any evidence in opposition to CMS' adjustment.

Incorporating the Low-Income Subsidy

Under the MMA, there will be a low-income subsidy program that provides premium and cost-sharing subsidies for Medicare beneficiaries fitting certain criteria. Initially, three groups were defined by some combination of the following: Medicaid eligibility status, income relative to the federal poverty level, and level of assets. In addition, institutionalized beneficiaries who are full-benefit dual eligibles are exempt from all cost-sharing (including premiums) and have no gap in coverage. When estimating the effect of the subsidy on spending, these three groups were combined into two groups.[11] Each of the groups will receive a somewhat different subsidy toward their premium, deductible, and copayments.

These benefits were included in order to address concerns as to how the new prescription drug benefit would affect spending requirements facing low-income beneficiaries. An additional concern vis-à-vis low-income beneficiaries is the willingness of plans to enroll them, given their expected higher spending levels. Any increased spending based solely on health status should be accounted for by the risk adjustment model through the diagnoses included. It is possible that an issue might arise if the impact on spending of a given diagnosis were different in the low-income population or if co-morbidities differ among low-income groups, given that the model was estimated on a non-low-income population. There may also be less straightforward behavioral components to being low-income (e.g., non-compliance with filling prescriptions) that have not been captured. However, if low-income beneficiaries have higher utilization and spending rates due to induced demand arising from a subsidized benefit, then MA plans or PDPs may be less amenable to enrolling these beneficiaries unless they are compensated accordingly. The policy issue then becomes how to appropriately estimate the size of this potentially higher payment needed on behalf of low-income beneficiaries.

Thus, in development of the risk adjustment model, an added complexity was in accurately measuring the level of induced demand from the low-income subsidy program. Because all persons in the FEP data faced a uniform benefit structure, the data were not appropriate for estimating induced demand; thus, this task was undertaken by the Office of the Actuary (OACT) at CMS using a different database (the Medicare Current Beneficiary Survey).

Spending Differences by Income

In order to accurately estimate induced demand, it would be useful to begin with estimates of raw spending for different income groups. While we have available data for both a *non*-low-income population (FEP enrollees) and a low-income population (Medicaid enrollees), these data sets could not easily be merged because of underlying differences in prices. Moreover, no data were available with which to explore spending in an uninsured,

[11] For the definition of the groups, see Table III-2 in the 45-day notice submitted by CMS and found at: http://www.cms.hhs.gov/healthplans/rates/2006/45-day.pdf

low-income population. Thus, direct comparisons between FEP spending and Medicaid spending do not readily support an estimate of the difference between utilization for these two different populations, as the difference is muddied by price differences and time differences at a minimum.

As a possible check on work being done at CMS, some additional runs were done using pooled 1997-2001 MCBS data. (Note that the MCBS contains no data on prescription drug spending for institutionalized beneficiaries, so this population was excluded from the analysis.) Two different sets of analyses were conducted. The purpose of the first was to examine the impact of age and Medicaid coverage on prescription drug use and spending. (The second of these analyses is described in the next section.) This analysis produced estimates of raw (unadjusted spending) and predicted spending (using the risk adjustment model) for different age-coverage subgroups of beneficiaries. Because of the small sample sizes, standard errors on the estimates are large and results should be viewed as suggestive only. Still, they support findings of substantial under-payment for the less-than-65 population. In this case, this is shown regardless of insurance status.

Estimating Low-income Induction

During the course of developing the estimates for induced demand, a number of different strategies were considered and the thinking on this issue evolved over several months. This process included considerable interaction among actuaries in OACT, the CMS economists developing the risk adjustment model, NORC staff, and Richard Kronick, a consultant to ASPE for this project. A number of issues made this process difficult, the lack of an appropriate database for estimation chief among them.

For these purposes, ideally one would want a data set that includes persons with a range of income levels as well as representing variation in benefit structure. The FEP data include no information on beneficiary income although it is reasonable to assume that most FEP enrollees are not low-income. In addition, all enrollees face the same benefit. The linked Medicaid-Medicare data, on the other hand, are made up entirely of low-income persons. It is not clear whether there is sufficient variation in the benefit structure across states to estimate induced demand from different levels of coverage. While the MCBS fits these criteria, sample sizes are relatively small for these purposes, the benefit structure for a given individual can only be inferred from observed spending, and drug prices are largely imputed.

In addition to the MCBS analysis described in the previous section, another MCBS analysis was undertaken to attempt to obtain estimates of the elasticity of demand for prescription drugs, to add to the information being used about induction. The analysis focused on persons who changed coverage from one year to the next and examined changes in spending after the coverage change. In order to do this, the assumption was made that changes in coverage were not correlated with health status; in other words, the change in coverage was treated as if it were exogenous. Using this approach, the weighted average elasticity of the number of prescriptions with respect to coinsurance was calculated for all individuals with an apparent change in drug coverage from one year to the next. The resulting implied elasticity was 77 percent--in other words, every percentage point reduction in coinsurance as a fraction of total spending leads to a 0.77 percent increase in the number of prescriptions. As an example, suppose a person spends a total of $1,000 with 50 percent coinsurance; if

you then eliminate the coinsurance, spending will increase to $1,385 [$385 = 1,000(.50 X .77]. It is important in viewing these results to understand that the implied elasticity for different population sub-groups varies substantially due to the small number of persons changing coverage. This result on induced demand was lower than that assumed by the actuary, at least at the time that this analysis was done.

The CMS Office of the Actuary estimated the effects of the low-cost sharing provided by the low-income subsidies on the spending of these groups. The most recent estimates available from CMS indicate adjustment factors of 1.08 and 1.05 for the two low-income groups.[12]

These adjustment factors were estimated using the 2001 MCBS, projected forward to 2006 and adjusted for a number of factors including under-reporting by households of drug expenditures, removal of discounts and rebates (standardizing prices to 'full retail'), applying a discount for management savings, and assuming an increase in expenditures due to the insurance benefit (induction).

There were some concerns expressed about these final low-income adjustments—whether they were accurate, how they compared to estimates obtained from Medicaid data, and the more strategic consideration of whether they would be sufficient to avoid discouraging plans from enrolling low-income beneficiaries. The specific methods used were fully accepted and, given data and time limitations, it was concluded that there were few alternatives available.

[12] For the definition of the groups, see Table III-2 in the 45-day notice submitted by CMS and found at: http://www.cms.hhs.gov/healthplans/rates/2006/45-day.pdf

Introduction

The new prescription drug benefit created by the MMA will be administered through private prescription drug plans (PDPs), which will collect both premiums from beneficiaries and payments from the Medicare program. In general, beneficiaries enrolled in the same plan in the same region will pay the same premium. However, Medicare's payments to plans will vary to incorporate differences in the cost of serving different beneficiaries. These adjustments will be critical to paying plans fairly for the services delivered and maintaining appropriate incentives for plans to serve all beneficiaries.

Statutory Requirements

The legislation names two specific types of plan payment adjustments. The most consequential adjustment in the payment system will likely be the risk adjuster, which will use information about beneficiaries' health to predict their use of prescription drugs and adjust plan payments accordingly. The legislation also 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*.[13] The Secretary is also charged with reporting to Congress on variations in per capita spending among PDP regions for covered Part D drugs.[14] 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.

The logic behind these potential adjustments is to protect beneficiaries from paying different amounts for drug coverage based simply on where they live. Like risk adjusters that are designed to ensure that beneficiaries do not face higher premiums because of their health status, a geographic adjuster would be established if drug prices varied by region, for example, because of differences in the cost of operating a pharmacy. It is easy to make a case that such adjusters are necessary if there are regional price differences. If there are regional differences in utilization, the case for making adjustments may depend on the reasons for these differences. If utilization is higher in one part of the country because of the prevalence of particular diseases (beyond that captured in the risk adjusters), then a good case can be made for making adjustments. By contrast, if drug use is higher because of the prescribing habits of physicians, policymakers may prefer to create pressure for these habits to change.

[13] Sec. 1860D-15.(c)(2)
[14] Sec. 107(a)

How Drug Pricing Works

When a customer pays for a prescription at the pharmacy counter, the drugs have already been through several transactions, each allowing for some opportunity for variation in price. Manufacturers generally establish a "manufacturer's average cost" (MAC), the publicly available list price for sale to wholesalers. However, manufacturers frequently offer discounts to wholesalers or other direct purchasers based on volume, prompt payment, or to create incentives to promote a particular brand. The government collects information on these discounted prices as the "average manufacturer's price" (AMP), but these data are not publicly available.

Wholesalers generally sell drugs to retail pharmacies at a markup over their cost. Database companies such as IMS Health and Verispan collect information from pharmacies about their acquisition costs for each drug. While confidentiality agreements preclude the publishing of data that would identify the acquisition price for any one drug, these data can be used to analyze acquisition prices for a group of drugs around the country to look for geographic variations in price at this point in the distribution chain. Variations in pharmacy acquisition prices might reflect, for example, higher transportation costs for pharmacies located farther from pharmaceutical manufacturers or wholesalers.

Retailers then sell drugs to consumers at a price that includes an additional markup. This markup generally includes a fixed dispensing fee, as well as a markup that may vary by drug. Geographic differences in these retail prices might reflect different costs of doing business, such as property costs or salaries.

Many pharmacy customers do not pay the full retail price. If a customer has third-party coverage for prescription drug costs, the pharmacy transaction will likely be at a discounted price. This third-party coverage is usually insurance coverage, but discount cards may also be used to provide customers access to these negotiated third-party prices. Third-party payers negotiate discounts in dispensing fees and other discounts that are reflected in the overall price paid at the point of sale. Data sets that collect drug price information generally allow analysis of these third-party transactions separate from transactions for customers paying the full retail price. Throughout this report, we will refer to customers with a third-party payment as "third-party" customers and those without a third-party payment as "cash" customers.

Third-party payers such as pharmacy benefit managers (PBMs) or insurance plans may also receive rebates paid directly from the manufacturer as an incentive to steer enrollees to certain drugs through the use of formularies, mail order, and other incentives. Information about these rebates is not typically available in data sets, as they are considered a proprietary transaction between the manufacturer and the third-party payer. As a result, we have not analyzed any information about manufacturer rebates for this report.

Geographic variations in spending depend not only on prices but also on utilization. While research has been done on variations in other health care utilization, less is known about how and why drug utilization varies around the country.

This report to ASPE provides information on geographic variation in both prices and spending relevant to the MMA's statutory requirements. In the first section, we analyze variations both in retail drug prices and in the prices that pharmacies pay to acquire prescription drugs. In the second section, we look at how spending by Medicare beneficiaries on prescription drugs varies by state.

Geographic Variation in Retail Prices

In this section, we examined data from retail pharmacy transactions to assess geographic variation in the prices that customers pay for prescription drugs. We found small differences among states in retail prices, with some evidence that there is larger variation within states, for customers without third-party coverage for their prescription drugs, and for generic drugs. We also examined possible explanatory variables for these differences.

Previously Published Evidence of Geographic Variation in Retail Drug Prices

Little has been published on geographic variations in retail drug pricing. Data reported by the National Association of Chain Drug Stores (NACDS) Foundation shows that the average cost of a prescription ranges by state from about $45 to about $65. This range of prices, however, reflects a variety of factors. Some, such as differences in the mix of drugs used or the length of the average prescription, are masking true price differences for the same quantity of the same drug. Other factors, such as varying overhead costs at different pharmacies, qualify as price differences. For example, the same report estimates that in 2002, state averages for dispensing fees ranged from $6.43 in Arkansas to $10.87 in Alaska.[15]

Other research has established that there are clear differences among prices paid by different types of purchasers. ASPE's *Report to the President on Prescription Drug Coverage, Spending, Utilization, and Prices* used both survey data (from the Medical Expenditure Panel Survey) and drug audit data (from IMS Health) to analyze differences between prices paid by consumers with third-party drug coverage and those without.[16] In 1999, the typical cash customer paid nearly 15 percent more than the customer with third party coverage at the point of sale, excluding the effect of rebates. The same report found some limited evidence that there is greater geographic variation in the prices charged to cash customers than in the prices charged to customers who have a third-party payment at the time of purchase.[17]

A recent study for the Healthcare Leadership Council found notable differences in current retail price levels for prescription drugs. Average retail prices in Maine (the lowest-priced state) were 15 percent lower than in Florida (the highest-priced state). However, the same

[15] National Association of Chain Drug Stores Foundation, 2003. The Chain Pharmacy Industry Profile.
[16] In the IMS data, the latter group includes those who paid cash, but filed paper claims with a third-party payer after the purchase. This type of purchase has become increasingly rare with the growth of electronic point-of-sale transactions.
[17] U.S. Department of Health and Human Services, April 2000. Report to the President; Prescription Drug Coverage, Spending, Utilization and Prices. Appendix C, page 206.

report found that many Medicare-approved discount cards tend to have one national price for each drug, suggesting that third-party payers are operating in a national market.[18]

Methodology

We examined data from IMS Health's National Prescription Audit™ (NPA™) database, representing an estimated 46 percent of all dispensed retail prescriptions in the United States. We excluded from the analysis any transactions reported by pharmacies that typically report a list price instead of the actual transaction price, resulting in a sample of 23,444 pharmacies. Additional information about the number of retail pharmacies and their distribution across states is in the Appendix as Figure A-1.

The pharmacy sample represents 44 percent of the pharmacies in the United States. It includes approximately 52 percent of all retail chain pharmacies and about 28 percent of all independent pharmacies. This varies by state. For example, coverage of independent pharmacies ranges from 6 percent for Delaware to 69 percent for North Dakota.

We looked at price data for a market basket of 62 drugs (52 brand and 10 generic) commonly used by Medicare beneficiaries. The list of drugs is included in the Appendix as Figure A-2. To create this market basket, we selected 16 therapeutic classes commonly used by the elderly, based on data from the NPA™, the National Disease and Therapeutic Index™, and NPA Market Dynamics™. The selected therapeutic categories account for nearly half of all dispensed prescriptions in long-term care pharmacies tracked by IMS Health for the six months ending June 2004. We then selected several of the most commonly used drugs within each therapeutic class. Three or more products were selected per category, because IMS Health is not permitted to show data that would identify individual products. Within each therapeutic class, the selected products range from 43.8% of the category to nearly 100% of the category.

We compared the selected products to the list of drugs most commonly used by Medicare beneficiaries that was included as an attachment to CMS's drug discount card solicitation. This list was compiled from the 2000 Medicare Current Beneficiary Survey. About two-thirds of the drugs on our list are also found on that list. Over half of the remaining drugs were approved for marketing in 1998 or later, so they were not available for use at the time of the survey or were newly approved and probably not yet widely adopted. A few others were included to ensure at least three products per class, as noted above.

We looked at only the most common form and strength of each drug during a three-month period ending June 2004. For generic products, we combined the data for the top two manufacturers of each product. We looked only at drugs dispensed by retail pharmacies, without mail order. The resulting sample included nearly 54 million transactions. Figure A-3 in the Appendix provides information about the number of prescriptions included in our sample.

[18] Bryant, Jennifer, John Corea, and Allison Sydlaske. "Assessment of Beneficiary Savings in the Medicare Drug Discount Card Program." Report prepared for the Healthcare Leadership Council. August 12, 2004.

For every drug in this market basket of 62 drugs, we calculated a price per pill for every prescription in the sample, by dividing the price paid for the prescription by the number of pills dispensed. We then calculated the median retail price per pill for each state. The quantity of pills dispensed for each prescription was used for weighting the per pill prices in determining the median prices. That is, if there were two prescriptions for the same product strength from the same state, one with a quantity of 30 pills dispensed and another with a quantity of 90 pills dispensed, the price per pill for the latter transaction would be weighted 3 times more heavily in the median.

For each state, we also calculated a weighted average of the median prices of pills in the market basket. To weight the drugs in the market basket, we used the estimated national volume of pills dispensed for the products from IMS' National Prescription Audit for the 2nd quarter 2004. The weights for determining the average median price, therefore, were the same for every state.

We divided the data into purchases made with a third-party payment at the time of payment ("third-party" purchases), purchases made by a customer paying the full price of the prescription ("cash" purchases), and purchases made by Medicaid beneficiaries. We have not focused on Medicaid purchases in this report because of the special pricing arrangements for prescription drugs in Medicaid. Prices paid by Medicaid customers are included in the calculation of median prices for all customers, but they are not included in the median prices for third-party customers.

When the data were divided in this way, there were some drugs that had a very small sample size in some states. Within each customer type, we chose to exclude drugs from the market basket for all states if one or more states had fewer than 50 transactions (prescriptions) for that product. As a result, the market basket for third-party purchases includes 58 drugs (50 brands/8 generics), and the market basket for cash purchases includes 43 drugs (38 brands/5 generics). We calculated the median price per pill for these purchases in each state.

Because of the different market baskets, the median price per pill is not directly comparable across different types of purchasers. We calculated an index value for each state, based on a scale in which the simple average of all states' median prices is equal to 1.00. These price indices create a standard measure for comparing variation even when the drugs or market baskets being considered are different.

Finally, we gathered data on several possible explanatory variables for the differences in prices. We selected the 15 states with the highest retail prices and the 15 states with the lowest overall retail prices (excluding Puerto Rico). For each set of factors we determined if the factor was greater or less in each of the two groupings of 15 states and tested the null hypothesis that the difference between the two means was zero. We also ran regression models to further explore the importance of certain factors.

Interstate Variation in Retail Drug Prices

The market basket average for the median retail price per pill is shown for each state, by customer type, in Figure 1. With a few notable exceptions, we found little variation among most states in the median price for all customers. Only three locations are more than 2 percent away from the average price for all states: North Dakota (4 percent above the

average), Hawaii (5 percent above the average), and Puerto Rico (10 percent above the average). The lowest median price is in Rhode Island (2 percent below the average). Despite this relatively small range, the difference between the 15 most expensive states and the 15 least expensive states is statistically significant, even after excluding Puerto Rico.

Looking at all customers together masks greater variation within specific customer groups. Consistent with previous research, there is more variation among states in the prices paid by cash customers than in third-party prices. In comparing these two groups of customers, it is important to look at the price indices, not the absolute price levels, because of the different market baskets. However, even the variation shown at this level may be affected by the mix of drugs in each market basket. The market basket for cash customers includes a higher proportion of generic drugs. As we will discuss in the next section, the variation in prices is much higher for generic drugs than for brand name drugs.

For purchasers with a third party payment for drugs, the index value ranges from 0.98 in Maine (2 percent below the average of all states) to 1.05 in Hawaii and 1.10 in Puerto Rico. Only five other states are more than 1 percent away from the average state: Rhode Island (-2%), Michigan (-2%), Massachusetts (+2%), North Dakota (+3%), and Hawaii (+5%).

In contrast, for cash customers, the index value varies from 0.93 in Montana (7 percent below the average of all states) to 1.12 in Delaware and 1.16 in Puerto Rico. Half the states are at least 3 percent away from the median of all states.

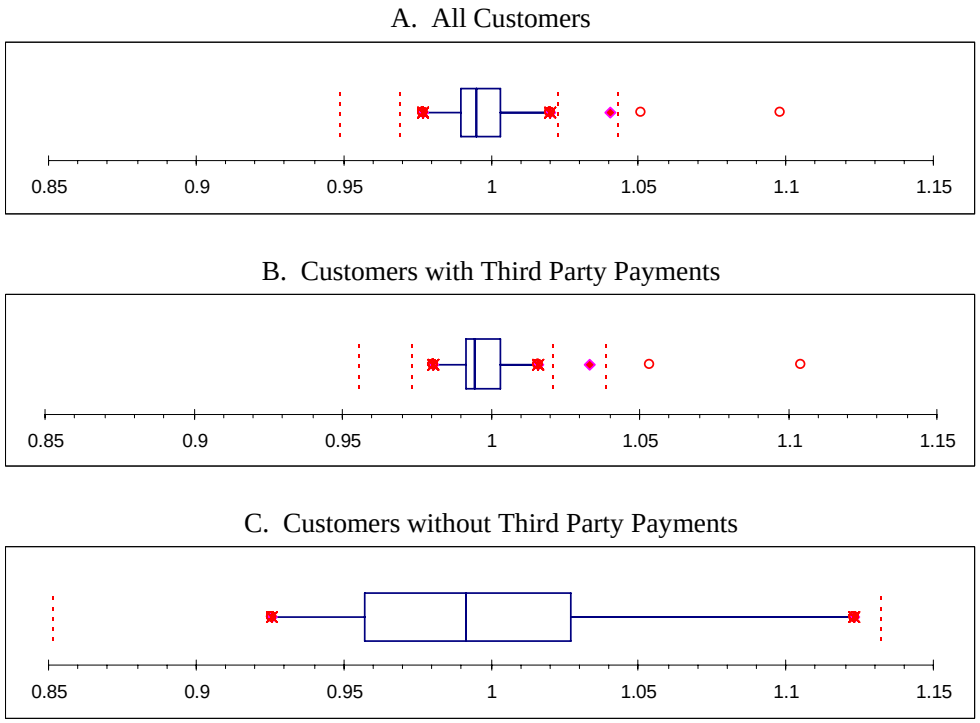
Figure 2 presents a graphic representation of the difference in the spread of retail prices for different customer segments. In these plots, the center line represents the median of the distribution of all states. The box surrounding the median represents the central 50 percent of states – the intraquartile range. The line extending to the left of the box represents the quartile of the distribution with the lowest prices, and the line extending to the right of the box represents the quartile of the distribution with the highest prices. Again, the prices cash customers pay vary much more by state than do the prices paid by third-party customers. Another way to measure the variation in prices is to look at the range and standard deviation as a percentage of the average of all prices. For all customers and for third-party customers, the range from the highest price to the lowest is $0.17, or 7 percent of the average. The standard deviation is $0.03, or 1 percent of the average. In contrast, the range for cash customers is $0.44, or 20 percent of the average. The standard deviation for cash customers is $0.11, or 5 percent of the average.

Figure 1. Average of Median Retail Price Per Pill for Drugs in the Market Basket, by State and Customer Type

	Price Index for All Customers (1)	Price Index for Third-Party Customers (2)	Price Index for Cash Customers (3)
Alabama	1.01	1.01	0.95
Alaska	1.02	1.00	1.02
Arizona	0.98	0.99	0.94
Arkansas	1.02	1.01	0.95
California	0.99	0.99	1.03
Colorado	0.99	0.99	1.01
Connecticut	0.99	0.99	1.06
Delaware	0.99	1.00	1.12
District of Columbia	1.00	1.00	1.10
Florida	0.99	0.99	0.98
Georgia	1.00	1.00	1.01
Hawaii	1.05	1.05	1.00
Idaho	0.99	0.99	0.96
Illinois	1.00	1.00	0.99
Indiana	0.99	0.99	0.99
Iowa	1.01	1.01	0.96
Kansas	1.00	0.99	0.97
Kentucky	1.00	0.99	0.96
Louisiana	1.02	1.01	0.99
Maine	0.98	0.98	1.06
Maryland	0.99	0.99	1.08
Massachusetts	1.01	1.02	1.09
Michigan	0.98	0.98	1.02
Minnesota	1.00	1.00	0.97
Mississippi	1.02	1.01	0.94
Missouri	1.00	0.99	0.96
Montana	1.00	1.00	0.93
Nebraska	1.00	1.00	0.95
Nevada	0.98	0.99	1.01
New Hampshire	0.98	0.99	1.06
New Jersey	0.99	0.99	1.07
New Mexico	0.99	0.99	1.01
New York	1.00	0.99	1.08
North Carolina	1.00	0.99	0.99
North Dakota	1.04	1.03	0.94
Ohio	0.99	0.99	0.98
Oklahoma	0.99	0.99	0.96
Oregon	0.99	0.99	0.97
Pennsylvania	0.99	0.99	1.08
Puerto Rico	1.10	1.10	1.16
Rhode Island	0.98	0.98	0.99
South Carolina	1.00	0.99	1.03
South Dakota	1.01	1.01	0.93
Tennessee	1.00	1.01	0.94
Texas	0.99	0.99	0.96
Utah	0.99	0.99	0.96
Vermont	1.01	1.01	1.03
Virginia	0.99	0.99	1.02
Washington	0.99	0.99	0.94
West Virginia	1.00	0.99	0.99
Wisconsin	0.99	1.00	0.98
Wyoming	1.01	1.00	0.95

(1) Index derived from state average of median prices of 52 brand and 10 generic drugs, weighted by volume of pills for all customers.
(2) Index derived from state average of median prices of 50 brand and 8 generic drugs, weighted by volume for third-party customers.
(3) Index derived from state average of median prices of 38 brand and 5 generic drugs, weighted by volume for cash customers.

Figure 2. Spread of State Retail Price Indices for Different Customer Segments



Variation by Brand and Generic Status

As might be expected, the prices for each individual drug show more variation from state to state than do prices for the market basket as a whole. In particular, the prices for generic drugs are much more variable. As a measure of this variability, we calculated the range of median prices for each drug: the difference in price from the most expensive state to the least expensive state. To make these ranges comparable across drugs, we then divided the range for each drug by the average of the prices for each drug. Figure 3 shows this measure for each drug in our market basket.

While the range in prices for a brand-name drug tends to be no more than 20 percent of the average, the range for generic drugs can be more than 100 percent of the average. That is, the difference between the price in the highest-cost state and the lowest-cost state can sometimes be more than the average price of the drug. However, the prices for these generic drugs are typically less than 50 cents per pill, while the prices for the brand name drugs are often much higher.

The prices of brand-name drugs tend to be highly correlated with each other as they vary from state to state. If brand drug A is more expensive than the national average in a particular state, other brand name drugs also tend to be more expensive in that state. For 20

states, the median price for each brand-name drug in our market basket is always at or above the national average; for another 21 states, the median price for each brand-name drug is always at or below the national average.

The prices of generic drugs do not show any notable correlation with brand name drugs or with each other. States may have a median price far below the national average for one generic drug, and far above the national average for another drug.

Intrastate Variation in Drug Prices

The overall lack of variability *among* states may also be masking a larger degree of variability *within* states. We looked at the interquartile range for all transactions within each state. To show them in a standardized format, we present the interquartile range of each state's transactions as a percentage of the median of all transactions for that state (see Figure 4).

The *inter*-state interquartile range for all customers is only one percent of the median. In contrast, the *intra*-state interquartile range ranges from a low of 4 percent to a high of 10 percent. This is a higher degree of variability, but the data still suggest that most drug prices are no more than 5 percent above or below that state's median price (though of course a smaller number of individual drug stores could have considerably higher or lower prices).

Similarly, while the interstate interquartile range for cash customers is 7 percent, the intrastate interquartile range is over 10 percent for all states but Delaware and South Carolina, and as high as 46 percent in Puerto Rico. For most states, this is still a modest amount of interstate variation, but it is again greater than the variation across states.

Correlates of Retail Price Variation

Despite the minimal differences in retail prices identified in this analysis, we considered whether any factors explained the small differences. Specifically, we looked for differences between the states with the highest retail prices and those with the lowest retail prices. Figure 5 shows the results of these tests. There are significant differences between the two groups of states (excluding Puerto Rico) in the proportion of the population living in a metropolitan area, median income, HMO penetration, and the number and types of pharmacies in the state.

Figure 3. Variation in Price by State, for Brand and Generic Drugs

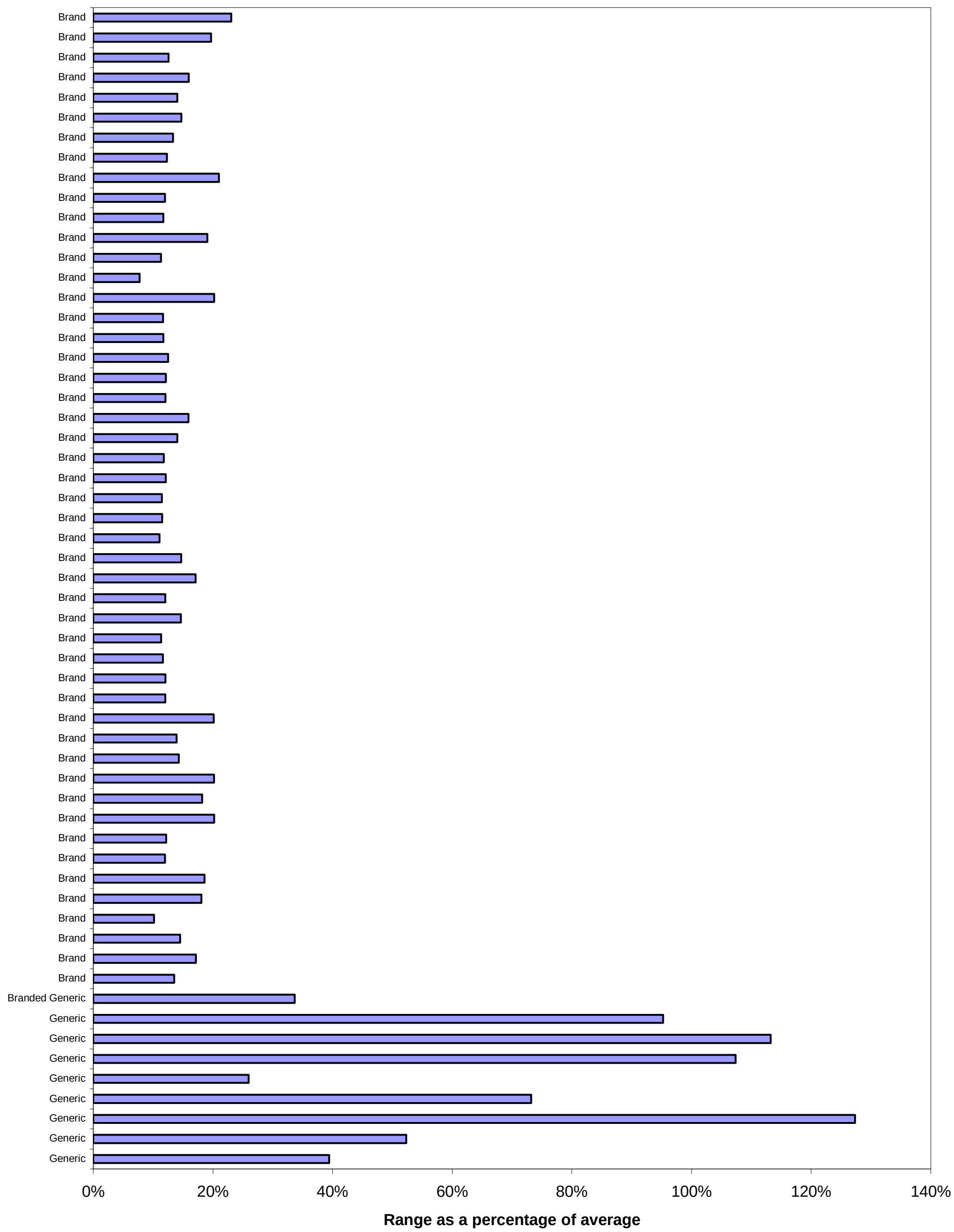

Brand
Branded Generic
Generic
0%
20%
40%
60%
80%
100%
120%
140%
Range as a percentage of average

Figure 4. Within-State Retail Price Variability[1], by State and Customer Segment

State	All Customers	Third Party Customers	Cash Customers
Alabama	5%	4%	16%
Alaska	10%	5%	16%
Arizona	4%	3%	18%
Arkansas	7%	4%	13%
California	6%	3%	22%
Colorado	5%	3%	14%
Connecticut	6%	4%	13%
Delaware	4%	3%	6%
District of Columbia	7%	3%	11%
Florida	7%	5%	16%
Georgia	5%	4%	14%
Hawaii	5%	5%	21%
Idaho	6%	4%	16%
Illinois	4%	3%	14%
Indiana	5%	3%	16%
Iowa	6%	4%	15%
Kansas	6%	4%	13%
Kentucky	7%	4%	15%
Louisiana	7%	5%	16%
Maine	5%	3%	11%
Maryland	4%	3%	14%
Massachusetts	8%	8%	12%
Michigan	5%	4%	15%
Minnesota	5%	3%	14%
Mississippi	6%	4%	16%
Missouri	9%	4%	15%
Montana	5%	3%	12%
Nebraska	6%	4%	14%
Nevada	5%	4%	17%
New Hampshire	5%	4%	14%
New Jersey	6%	4%	14%
New Mexico	5%	4%	17%
New York	7%	3%	13%
North Carolina	9%	3%	15%
North Dakota	8%	7%	11%
Ohio	5%	3%	17%
Oklahoma	6%	4%	11%
Oregon	4%	3%	20%
Pennsylvania	5%	4%	14%
Puerto Rico	8%	6%	46%
Rhode Island	4%	3%	13%
South Carolina	8%	3%	8%
South Dakota	7%	4%	12%
Tennessee	3%	3%	15%
Texas	5%	4%	13%
Utah	5%	3%	23%
Vermont	5%	3%	13%
Virginia	6%	4%	17%
Washington	5%	3%	22%
West Virginia	6%	3%	16%
Wisconsin	6%	4%	15%
Wyoming	7%	4%	12%

(1) Intrastate retail price variability is measured as the interquartile range of retail prices shown as a percentage of the median retail price. Price percentiles are derived separately by product within state, and weighted averages are computed across products using estimated national unit volumes for each product/customer segment for weights.

Several of these factors could suggest that prices are somewhat lower in areas with a greater potential for generating competition. States with the lowest prices have a significantly higher percentage of their populations living in a metropolitan area (80% vs. 54%). Low-price states also have significantly higher median income ($46,521 vs. $41,079) and a significantly higher HMO penetration rate (26% vs. 11%), both factors that are correlated with the percentage of the population living in metropolitan areas.

But if competition is the key, one would expect lower prices where there are more pharmacies competing to serve the same population. Instead, low-price states had fewer pharmacies (18 vs. 22 per 100,000 population). The number of pharmacies per capita seems to be related to the cost of operating a pharmacy; the measure is negatively correlated with pharmacist wages (r=-.50) and apartment rents (r=-.73). This could help explain the counterintuitive result that these two measures of pharmacy costs are actually higher in low-price states. Low-price states have significantly higher pharmacist wages than high-price states ($77,792 vs. $73,608) and significantly higher monthly rents ($615 vs. $523).

There are highly significant differences between the two groups of states in the types of pharmacies that make up their markets. Low-price states have fewer independent pharmacies (26% vs. 47%) and more chain and supermarket pharmacies. The percentage of pharmacies that are chain or independent is correlated with the percentage of people living in a metropolitan area; states with a more metropolitan population are more likely to have chain pharmacies (r=.57) and less likely to have independent pharmacies (r=-.59).

We tested several different regression models in which the dependent variable was the median price per pill for all customers. The proportion of pharmacies that are chain or independent was always highly significant in our models, with an increase in independent pharmacies increasing a state's median price. (We did not use both in a regression at once because they are so highly correlated.) Property rents were also significant in all of our regressions. When controlling for other variables, an increase in rents increases a state's median price per pill, reversing the direction of the association noted above. These relationships are consistent with the idea that the cost of operating a pharmacy is a key factor influencing prices.

After controlling for the mix of pharmacy types, a state's metropolitan residence and median income were not statistically significant, nor were pharmacist wages and pharmacies per capita. The HMO penetration rate sometimes was significant, depending on the model.

Figure 5. Differences Between the Most Expensive and Least Expensive States

Factor	Mean for the 15 states with the lowest prices	Mean for the 15 states with the highest prices	t and p-value (two tailed)
Market basket price per pill for all customers**	**$2.21**	**$2.28**	**7.76 t** <.0001 p-value**
Population density (number per square mile)	298	121	-1.63 t .1152 p-value
Percent of the population living in a metropolitan area **	**80 %**	**54 %**	**-3.62 t ** .0012 p-value**
Percent with a Bachelor's degree or higher	28 %	25 %	-1.84 t .0765 p-value
Median income *	**$46,521**	**$41,079**	**-2.18 t* .0381 p-value**
Medicare beneficiaries as a percent of population	13.9 %	14.5 %	0.81 t .4252 p-value
Medicaid beneficiaries as a percent of population	0.14 %	0.16 %	1.67 t .1062 p-value
Percent of the population aged 19-64 with employer coverage	69%	67%	-1.17 t .2530 p-value
Percent of the population aged 19-64 uninsured	17.6%	17.5%	-0.07 t .9414 p-value
HMO Penetration rate **	**26 %**	**11%**	**-4.18 t ** .0003 p-value**
Pharmacists per 1,000 population	1.51	1.55	0.16 t .8720 p-value
Pharmacies per 1,000 population*	**.18**	**.22**	**2.45 t* .0207 p-value**
Chain pharmacies as percent of all pharmacies**	**42%**	**26%**	**-3.20 t** .0033 p-value**
Mass merchant pharmacies as percent of all pharmacies	11%	13%	1.07 t .2905 p-value
Supermarket pharmacies as a percent of all pharmacies*	**20%**	**14%**	**-2.27 t* .0312 p-value**
Independent pharmacies as a percent of all pharmacies**	**26%**	**47%**	**5.11 t** <.0001 p-value**
Median annual pharmacists wages*	**$77,792**	**$73,608**	**-2.58 t* .0154 p-value**
Median monthly apartment rent*	**$615**	**$523**	**-2.51* .0179 p-value**

* Significant at the .05 level
** Significant at the .01 level
Sources listed in Appendix in Figure A-4.

Because retail price differences among states are minimal, it was unlikely that a search for explanatory factors would be highly revealing. The univariate explanations, in particular, failed to shed much helpful light. The multivariate analysis seems somewhat more enlightening, reinforcing the expectation that input costs faced by pharmacies are one of the few factors explaining price differences.

Policy Considerations and Areas for Further Research on Retail Price Differences

The third-party retail price (as opposed to the price paid by other types of customers) is probably the most appropriate baseline for looking at geographic variation as it might affect Part D. Third-party prices reflect retail sales prices negotiated by health plans, just as prescription drug plans will negotiate in Medicare Part D. Because the geographic variation in retail prices paid by third-party payers is minimal, a plan payment adjustment for geographic variation in drug prices may be unnecessary.

What variation does exist at the state level is seen most strongly in Puerto Rico, Hawaii, and North Dakota. In designating regions for Medicare Part D, North Dakota is grouped in a region with a total of seven states. As a result, its higher prices will be averaged with prices in the other states and should not have a substantial impact on plan premiums. By contrast, Hawaii and Puerto Rico have both been designated as their own regions. As a result, the Department may want to monitor and explore further whether the higher drug prices faced by residents of Hawaii and Puerto Rico may lead to significantly higher premiums. If higher prices occur under Medicare Part D, some adjustment may become necessary.

To the extent that there are differences in price, our testing of explanatory variables suggests that states with a higher proportion of independent pharmacies – which tend to have a lower proportion of their populations living in metropolitan areas – tend to have higher retail prices. Medicare does not typically use ownership status as a payment adjustment factor. However, when controlling for other factors, areas with higher property rents also seem to have higher retail prices. This is a factor that has been used to make geographic adjustments in other Medicare payment systems.

Some evidence presented here (and similar evidence from other studies) suggests that price variation is greater within states than across states. Further research is needed to see if prices are higher, for example, in rural areas compared to urban areas. Although this question is an interesting one, it is less relevant to Medicare payment since the MMA defines regions as states or groups of states. Thus, plans must offer drug benefits to all beneficiaries living in a given state and may not vary the premium based on where in the state someone lives.

Further exploration also seems warranted to monitor price variation under Medicare Part D. This benefit will be structured differently than the current market, and the nature of competition could vary substantially from region to region. Competition by itself should lead to premium variation across the country, but it will be important to monitor whether price differences are one source of this variation. To the extent that price variation increases, however, it will be difficult to disentangle the effects of plan competition on prices paid from underlying price differences.

Geographic Variation in Acquisition Prices for Retail Pharmacies

The previous section detailed how prices vary at the retail counter. This section of the report examines prices one step earlier in the distribution chain – the price pharmacies pay to wholesalers or manufacturers. In this section, we look first at retail pharmacies. We then compare the acquisition prices paid by retail pharmacies to other types of pharmacies, such as hospitals and clinics.

Previously Published Evidence of Geographic Variation in Acquisition Drug Prices

In a study of invoices at Medicaid pharmacies in eight states, the HHS Inspector General found small variations by state in the prices pharmacies paid to wholesalers for drugs. For brand name drugs, pharmacies paid from 19.64 percent (Colorado) to 22.88 (Florida) percent below AWP. For generic drugs, pharmacies paid from 62.84 percent (Texas) to 68.92 percent (West Virginia) below AWP.[19]

Some large pharmacy chains, hospitals, and HMOs may deal directly with manufacturers, bypassing wholesalers and receiving their own negotiated discounts. Several years ago, the Congressional Budget Office (CBO) used IMS Health data to estimate differences in the prices paid by retail pharmacies compared to those paid by bulk purchasers such as HMOs or hospitals. The study found that hospitals typically paid 91 percent of what retail pharmacies paid, and HMOs paid 82 percent.[20] However, this study did not examine whether there were any geographic differences in the price variations.

Methodology

For acquisition prices paid by retail pharmacies, we examined data from the IMS Health National Sales Perspectives™ database. In the retail price analysis, each retail transaction was one observation, resulting in thousands of data points. In this acquisition price database, however, each pharmacy reports a price for each drug only when it makes a purchase of the drug from a wholesaler or manufacturer. As a result, we have many fewer observations for each drug, depending on the number of pharmacies in the sample. To improve sample sizes, we collapsed all states into the ten administrative regions used by HHS (see Figure A-5). We examined acquisition prices for the same market basket of drugs we used to look at retail sales prices. However, one generic product was excluded from this analysis of acquisition prices due to a small number of observations.
For acquisition prices paid by non-retail pharmacies, we examined data from IMS Health's National Sales Perspectives™ Non-Retail database for purchases made by non-federal hospitals, long-term care facilities, and clinics. Again, we collapsed the data into the ten

[19] Department of Health and Human Services, Office of the Inspector General. "Review of Pharmacy Acquisition Costs for Drugs Reimbursed Under the Medicaid Prescription Drug Program" for Washington (November 19, 2001), Colorado (November 28, 2001), Texas (November 29, 2001), West Virginia (December 27, 2001), Indiana (December 31, 2001), Montana (February 7, 2002), Florida (February 25, 2002), and Wisconsin (March 5, 2002).
[20] CBO, July 1998. How Increased Competition from Generic Drugs Has Affected Prices and Returns in the Pharmaceutical Industry.

HHS regions to improve our sample size for each drug. This database also includes federal facilities, HMOs, home health agencies, and miscellaneous pharmacies, but there were not enough observations in some regions to include those types of pharmacies in our analysis.

We attempted to examine the same market basket of drugs we used to look at retail pharmacy acquisition prices. Three brand-name products and all generic products were excluded from this analysis, due to a small number of observations. There are 49 remaining brand-name products in the market basket used for our analysis of the variation in prices across multiple types of pharmacies. Because the market basket changed slightly from the retail sales price analysis, the acquisition prices are not directly comparable to the retail prices used in the previous section.

Regional Variation in Acquisition Prices for Retail Pharmacies

Figure 6 shows the acquisition price reported by the retail pharmacies in our sample for the products in the market basket. The range of variation in the retail price index is even smaller for these acquisition prices than it is for retail prices charged to customers with a third-party payment. No region is more than one percent above or below the average. However, consolidating states into regions may be masking some variation that exists at the state level.

Variation in Acquisition Prices for Different Types of Pharmacies

Our findings confirm previous findings that there are differences between purchasers in the acquisition prices they pay. Figure 6 shows the median acquisition price per pill for each type of purchaser, by HHS region. Each is for an average of the prices of the 49 drugs in the common market basket for this analysis. Thus, the median prices in this table are comparable across purchasers within the table.

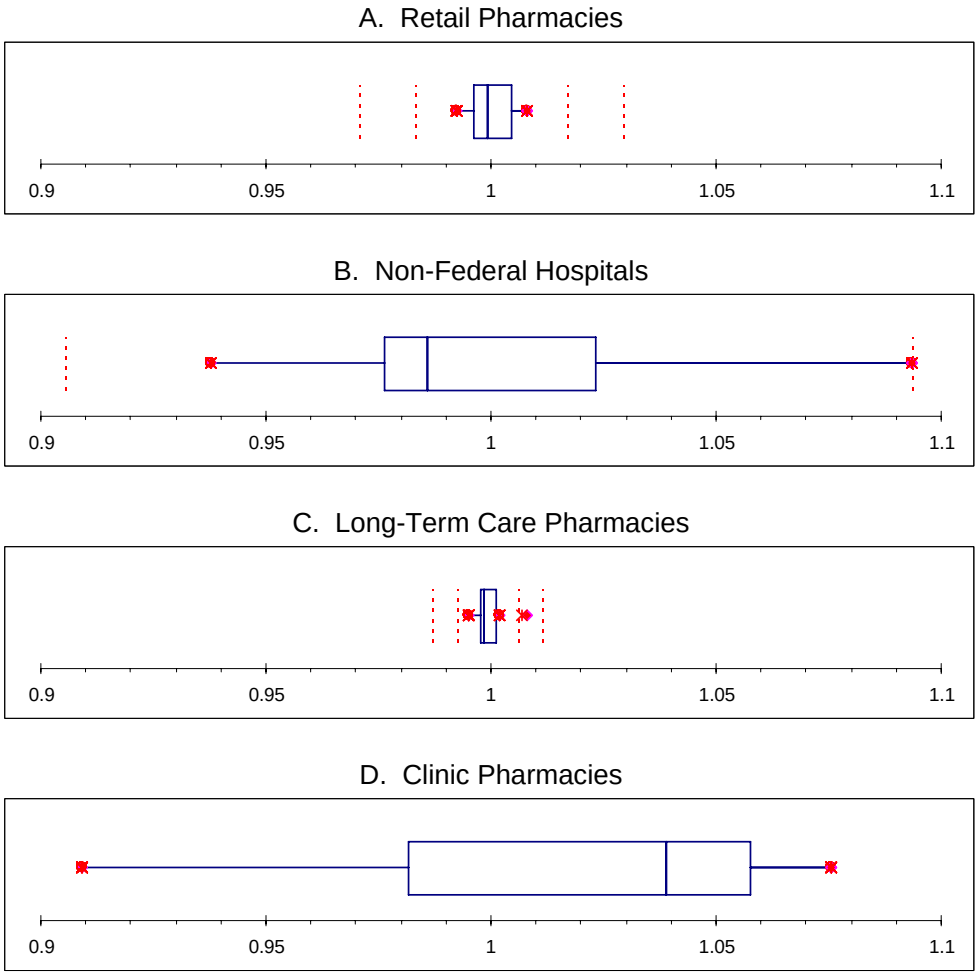
We found that non-federal hospitals paid only 74 percent of what retail pharmacies paid for the drugs in this market basket. Long-term care pharmacies' acquisition costs were 98 percent of retail pharmacies' costs, and clinics' acquisition costs were 87 percent. Although the level of the difference varies across regions, there is no region in which the median for retail pharmacy acquisition costs is lower than the acquisition cost paid by other types of pharmacies in our sample.

Like retail pharmacies, pharmacies at long-term care facilities experience little variation at the region level. In contrast, non-federal hospitals and clinics appear to experience considerably more geographic variation in acquisition price. Figure 7 shows the spread of acquisition prices for different purchasers by plotting the quartiles. No explanation is immediately evident for why there is a greater regional spread of acquisition prices for hospitals and clinics than for retail and long-term care pharmacies. There is regional diversity in the hospital industry; for example, hospitals in some regions are more likely to be for-profit entities and more likely to be part of large hospital chains. Similarly, clinics play different roles in different areas. For example, some cities have large networks of community health centers, while other cities have few or none. It may be that these ownership and structural differences influence their ability to negotiate drug prices.

Figure 6. Acquisition Price by HHS Region and Purchaser

HHS Region	Retail		Non-Federal Hospitals		Long Term Care		Clinics	
	Median Acquisition Price per Pill	Price Index	Median Acquisition Price per Pill	Price Index	Median Acquisition Price per Pill	Price Index	Median Acquisition Price per Pill	Price Index
1 (CT, ME, MA, NH, RI, VT)	2.44	1.00	1.71	0.94	2.39	1.00	2.29	1.07
2 (NJ, NY, PR)	2.43	0.99	1.80	0.99	2.39	1.00	2.26	1.05
3 (DE, DC, MD, PA, VA, WV)	2.44	0.99	1.81	0.99	2.40	1.00	2.09	0.98
4 (AL, FL, GA, KY, MS, NC, SC, TN)	2.44	1.00	1.88	1.03	2.39	1.00	1.68	0.78
5 (IL, IN, MI, MN, OH, WI)	2.46	1.00	1.77	0.97	2.39	1.00	2.30	1.08
6 (AR, LA, NM, OK, TX)	2.45	1.00	1.77	0.97	2.41	1.01	2.26	1.06
7 (IA, KS, MO, NE)	2.45	1.00	1.79	0.98	2.41	1.01	2.24	1.05
8 (CO, MT, ND, SD, UT, WY)	2.46	1.01	1.99	1.09	2.38	1.00	1.94	0.91
9 (AZ, CA, HI, NV)	2.46	1.01	1.90	1.04	2.39	1.00	2.13	0.99
10 (AK, ID, OR, WA)	2.47	1.01	1.79	0.98	2.39	1.00	2.21	1.03
Average	2.45		1.82		2.40		2.14	

Figure 7. Spread Across Regions of Acquisition Prices for Different Purchasers



What is clear is that the price differences observed do not reveal a uniform regional pattern. There is very little correlation between the acquisition prices paid by different types of purchasers by region. In particular, regions with a high price for hospital pharmacies have low prices for clinic pharmacies, and vice versa. We are not aware of an explanation for why this might be the case.

Policy Considerations and Areas for Further Research on Acquisition Price Differences

The low level of regional variation in acquisition prices is in keeping with the low level of variation in retail prices described in the previous section. However, it is not clear from this analysis whether acquisition prices might vary more at the state level than do retail

prices. Further research could be warranted in this area to determine whether retail price variations are related to acquisition price or are caused by other factors.

In many ways, acquisition price variation is more salient than retail price variation to the question of whether Medicare should incorporate a price adjuster for Part D. The retail price paid on behalf of the consumer (combining the consumer's cost sharing with the plan's payment) is normally set by the plan (at least for pharmacies participating in the plan's network), while the pharmacy's acquisition price is determined by a broader set of factors. Still, acquisition prices are often influenced by plan negotiations. Some health plans (e.g., Kaiser Permanente) operate their own pharmacies, in which case they negotiate acquisition prices in conjunction with their ability to manage utilization through tools such as formularies. To a lesser extent, health plans may be able to use their negotiations with pharmacies to allow pharmacies to obtain preferred drugs at lower prices.

Fortunately for policymakers, the conclusion is the same. Like the retail price analysis, the analysis here supports the conclusion that variation is *de minimis* and that geographic price adjustment may not be necessary. But as noted in the discussion of retail prices, the new Medicare benefit is likely to have a major impact on market forces. Accordingly, it will be important to monitor the patterns of acquisition prices and to revisit the question of geographic variation after implementation of Medicare Part D.

Geographic Variation in Drug Spending

While drug prices may not vary much by geography, the general evidence in the literature suggests that utilization and spending vary more. To the extent that geographic variation in spending is not explained by variables that are factored into plan payments, beneficiaries in areas with higher utilization may pay higher premiums for drug coverage under Part D. In this section, we examine data for Medicare retirees from Blue Cross Blue Shield's Federal Employee Plan for evidence of geographic variation in drug spending. In particular, we explore whether the geographic differences can be accounted for by health status as measured by the risk adjustment factors to be used in Medicare Part D. We then examine several variables that could explain any remaining differences.

Previously Published Evidence of Geographic Variation in Drug Spending

Numerous studies have shown marked geographic variation in utilization of health care services, even after demographic and health status factors are taken into account. For example, Wennberg *et al.* found that differences in health status explain just 27 percent of the variation in Medicare spending across regions.[21] The remaining variation is attributed to a wide variety of influences, from the supply of physicians and differences in their styles of practice, to climate and culture.

[21] Wennberg, John E., Elliott S. Fisher, and Jonathan S. Skinner, 2002. "Geography and the Debate Over Medicare Reform." Health Affairs Web Exclusive.

Less research has been done to determine the extent of variations in prescription drug utilization. Whereas the national system of distribution for drugs seems to limit geographic variation in drug prices, the factors influencing utilization might operate just as strongly on drug use as on the use of other health care services. Express Scripts studied geographic variation in drug use in 1999 for a random sample of their commercially insured members ages 18 to 65. The likelihood that a member would use at least one prescription varied from 71 percent in the highest-use state to 58 percent in the lowest-use state. Similarly, the number of prescriptions per member per year varied from 12.2 to 8.3.[22] In a peer-reviewed study, Dubois *et al.* examined administrative claims data from three California health plans for April 1998 through September 1999 and compared enrollees across 11 regions of California. This study suggests that within large states, there can also be differences in drug use. Across all drugs studied, the ratio of highest-use to lowest-use was 1.77.[23]

ASPE's 2000 report also found regional variations in prescription drug spending, based on analysis of 1996 MEPS data. This analysis found that residents of the Midwest and South filled more prescriptions and had higher total spending per person than residents of the West and Northeast. The variation in drug spending was slightly different from that in total health care spending.[24]

Previous studies have found that geographic variation is larger within therapeutic classes of drugs than it is across all classes of drugs. In the Express Scripts study, calcium channel blockers saw the greatest variation, with a prevalence of 5.3 prescriptions in the highest-use state and 1.3 prescriptions in the lowest-use state.[25] The California study found the highest amount of geographic variation in the use of Cox-2 inhibitors, with a ratio of 2.57 between the highest-use and lowest-use area. The use of diuretics, coumadin, and digoxin for congestive heart failure was twice as common in the highest-use area of California as in the lowest-use area.[26]

There is some preliminary evidence that related health indicators do not always predict drug utilization as well as might be expected. For example, Express Scripts found that only 21 percent of the variation of use of diabetes drugs was related to the prevalence of diabetes by state, whereas the risk of heart disease explained 62 percent of the variation in utilization of cardiovascular medications.[27]

Methodology

We used claims data for Medicare beneficiaries (age 65 and over) included in Blue Cross/Blue Shield's Federal Employee Plan (FEP) for our analysis of beneficiary spending on all prescription drugs by state for 2002. Because Medicare does not cover outpatient

[22] Motheral, Brenda, Emily R. Cox, Doug Mager, Rochelle Henderson, and Ruth Martinez, January 2002. Express Scripts Prescription Drug Atlas. http://www.express-scripts.com/other/news_views/outcomes_research/atlas/atlas_view.htm
[23] Dubois, Robert, Elaine Batchlor, and Sally Wade, 2002. "Geographic Variation in the Use of Medications: Is Uniformity Good News or Bad?" Health Affairs Volume 21, Number 1, pp. 240-249.
[24] DHHS, Report to the President. Appendix C, pages 204-205.
[25] Motheral et al., Express Scripts Prescription Drug Atlas.
[26] Dubois et al., "Geographic Variation in the Use of Medications: Is Uniformity Good News or Bad?"
[27] Motheral et al., Express Scripts Prescription Drug Atlas.

drugs, these data should cover all drug use for these FEP enrollees. The FEP data file included total unadjusted per person spending as well as individual drug claims. The individual drug claims did not have dollar amounts attached, so we could only look at spending in total. Further research could work from the claim-level data and attach prices from a separate source to look at spending at the level for specific drugs or classes of drugs.

We looked at spending in the federal insurance program in several different ways.

- First, we looked at *unadjusted FEP plan spending* for 2002, as provided on the original FEP file. This amount includes the amounts paid by the plan and excludes enrollee cost sharing.

- Second, we calculated *projected plan spending* for the 2006 Medicare Part D benefit structure, based on the FEP spending. In doing so, we considered the impact of the Part D deductible, initial coverage period, coverage gap, and catastrophic coverage. The result includes only the plan portion of the spending, but excludes the effect of risk adjustment and net of the effect of the federal government's reinsurance or risk sharing payments. In making this calculation, we also inflated the 2002 amounts to 2006 levels, using an annual growth rate of about 11 to 12 percent. Finally, we added an amount ($300) per person that would serve as an estimate of annual overhead expenses for the plan.[28] The absolute levels of projected 2006 spending are lower than those for 2002 FEP spending, despite the substantial rates of inflation, because the Medicare Part D benefit is considerably thinner than that in the federal employees plan. The large deductible and coverage gap do not have parallels in the design of the latter plan.

- Third, we calculated *risk-adjusted plan spending*. This amount is calculated by multiplying the projected plan spending (including overhead) by the ratio of predicted plan spending for the state to predicted national plan spending. Predicted plan spending for each person in the file was based on the various factors in the CMS risk-adjustment model (January 2005 version), including diagnoses and other factors.[29] Predicted national spending was calculated in the same way.

- Finally, we calculated an estimated *beneficiary premium* for each state for beneficiaries enrolled in Medicare Part D. To estimate the premium, we assumed that the projected plan spending in a state is the basis for how a plan serving that state would estimate its costs and thus its bid premium. Based on the formula specified in law, enrollees must pay a base national premium plus the difference between their plan's bid and the nationwide average of bids to provide the standard benefit. In this case, we used risk-adjusted plan spending (with overhead included) as a proxy for the bid

[28] We assumed that each plan's overhead would be the same regardless of average spending in the state. An alternate assumption would to calculate overhead as a percentage of average spending. This would tend to inflate the amount of state variation since states with higher spending would also have higher overhead costs.
[29] In calculating predicted spending from the FEP drug spending and relevant diagnostic data, we made the following adjustments: (1) people who were not in Medicare for 12 months in a year were excluded, (2) people who were not in both Part A and Part B were excluded, (3) people who had Medicaid buy-ins were excluded, and (4) people under 65 were excluded.

of a plan in a given state. Similarly, we used risk-adjusted national spending as a proxy for the nationwide average. The beneficiary premium is calculated as the base beneficiary premium (34 percent of the national average premium), adjusted for the difference between the plan bid and the national average bid amount (which may be negative or positive).[30]

After examining the variation in state spending in a variety of ways, we explored possible explanatory variables. We selected the 15 states with the highest spending and the 15 states with the lowest spending. For each possible explanatory variable, we calculated a mean for each of the two groupings of 15 states and tested the null hypothesis that the difference between the two means was zero. We also ran regression models to further explore the importance of certain factors.

Overall Geographic Variation in Drug Spending

Plan spending reveals a considerably larger range of geographic variation than did drug prices, as shown in Figure 8. In this table, we show two ratios, one of the third quartile value to the first quartile and one of the maximum value to the minimum. Because the latter can be skewed by a single small or large value, more emphasis should be given to the former measure. Even risk-adjusted spending, which shows the least variation (1.07) far exceeds that 1.01 value for either of the price measures derived from the analysis in the previous section.

Figure 8. Range of Geographic Variation for Several Measures of Plan Spending

	Interquartile Range (Ratio of Quartile 3 to Quartile 1)	Range (Ratio of Maximum to Minimum)
Unadjusted FEP Plan Spending, 2002	1.18	1.41
Projected Plan Spending, 2006	1.11	1.27
Risk-Adjusted Plan Spending, 2006	1.07	1.21
Beneficiary Premium, 2006	1.23	1.81
Retail Prices, Third-Party Customers, by State	1.01	1.12
Acquisition Prices, Retail Pharmacies, by Region	1.01	1.02

The different measures of spending reported in Figure 8 reveal the story of geographic variation in different ways. First, unadjusted spending for the federal retirees insured by the Blue Cross/Blue Shield Federal Employees plan shows the greatest variation of the three spending measures. FEP spending ranged from $1,441 per person in North Dakota (18% below the national average) to $2,034 per person in Indiana (15% above the national average) in 2002. The average person in Indiana incurs 41 percent more in drug costs than someone in North Dakota. Among the middle half of the states, the highest is 18 percent above the lowest. This measure shows how spending varies across states in the purest sense.

[30] The 34 percent factor results from adjusting the 25.5 percent beneficiary share of the overall cost of the benefit for the federal reinsurance amounts that are not included in the plan bid amounts.

By contrast, the 2006 projected plan spending measure accounts for the fact that most of the spending under the design of the Medicare drug benefit occurs in the initial coverage period (up to $2,250 in total spending in 2006) and excludes much of the spending above that level. Under the Part D benefit, we project that plan spending would range from $1,362 in Alaska (16% below the national average) to $1,724 in Indiana (7% above the national average). We can infer from the lower ratios (1.11 versus 1.18 for the interquartile range and 1.27 versus 1.41 for the overall range) that an important source of variation for high-spending states is probably a greater number of high spenders (above $2,250 in total spending). Their reduced importance under the benefit design results in less geographic variation.

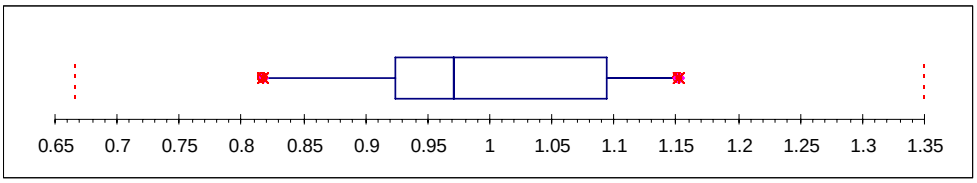
The amount of geographic variation is further reduced when looking at risk-adjusted plan spending. After risk adjustment, projected plan spending ranges from $1,434 in New York (11% below the national average) to $1,739 in Indiana (8% above the national average). Using this measure, the highest-spending state (Indiana) is only 21 percent above the lowest-spending state (New York), and the ratio of the quartiles is only 1.07. This reduction in variation is expected if one of the sources of state-to-state differences is the varying prevalence of the health conditions that drive drug utilization. The risk adjustment system in use for the Medicare benefit is based primarily on the appearance of different diagnoses on individuals' medical records. But since the geographic variation is not reduced to inconsequential levels, it seems clear that either the risk adjusters are not fully capturing the health status differences across states or that there is some other important source of variation. These alternatives are discussed further below.

The variation in the projected beneficiary premiums is greater than for any of the other spending measures. The statutory formula for calculating the premium largely drives this result. The law's intent is that beneficiaries should be required to pay more for a more expensive, less efficient plan and less for a cheaper, more efficient plan. The risk adjustment system is designed to correct for a plan that costs more because it attracts enrollees with poorer health status. But if it turns out that geographic variation remains after risk adjusters are applied (as in our data), then beneficiaries in more expensive states will pay the entire difference. Furthermore, the degree of variation is exaggerated beyond that in the underlying spending data (see the section below for more on the impact of geographic differences on premiums).

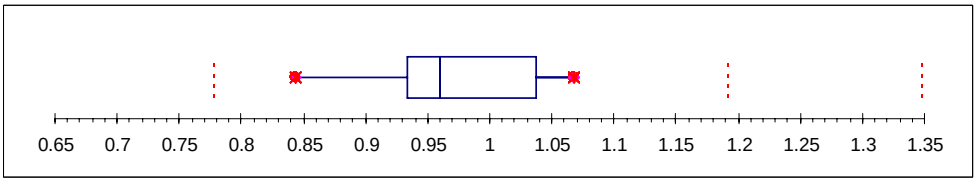
Figure 9 shows graphically the range of geographic variation revealed by these four measures of spending. The figure displays the quartiles of each distribution of state-level spending and shows how the distribution of risk-adjusted spending is less skewed and narrower than the distribution of either unadjusted 2006 spending or 2002 FEP spending. It also reemphasizes how the formula for beneficiary premiums causes a wider spread among the states. The variation in all measures of spending is greater than the variation in overall prices shown in the first section of this report.

Figure 9. Variation in Spending as a Proportion of Average Spending

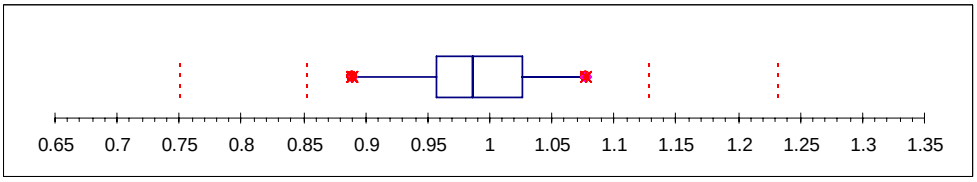
A. Unadjusted FEP Plan Spending, 2002



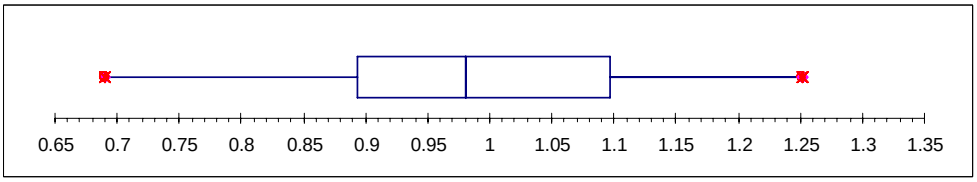
B. Projected Plan Spending, 2006



C. Risk-Adjusted Plan Spending, 2006



D. Beneficiary Premiums, 2006



State-Level Differences

One way to view the patterns of variation is to look at the array of states and how the rank-ordering of states shifts across the different measures of spending. Figure 10 shows 2002 FEP spending and 2006 projected drug plan spending by state (as well as the risk-adjusted 2006 spending and projected 2006 beneficiary premiums). While the change from actual 2002 spending to projected 2006 spending changes the range of variation across all states, the relative position of states is quite similar using either of the two measures. The correlation between states' average 2002 spending and projected 2006 spending is 0.99.

However, risk adjustment changes the relative position of states quite noticeably. Figure 11 shows the rank ordering of states before and after risk adjustment. The simple correlation between the state averages for adjusted and unadjusted spending is 0.80.

Seven states move down ten places or more, meaning that they are relatively more expensive after risk adjustment is applied: Minnesota, Colorado, Montana, Wyoming, Alaska, Idaho, and Oregon. Eight states move up ten places or more (are relatively less expensive): Massachusetts, Rhode Island, New Jersey, New York, Delaware, Washington, DC, Pennsylvania, and Florida.

Other states are relatively stable in their rank order despite risk adjustment. Twelve of the fifteen highest-spending states before risk adjustment remain in the top fifteen after risk adjustment: Alabama, Georgia, Indiana, South Carolina, Oklahoma, Louisiana, West Virginia, Kentucky, Utah, Tennessee, North Carolina, and Mississippi. Eleven of the fifteen lowest-spending states before risk adjustment remain in the bottom fifteen after risk adjustment: Maine, Wisconsin, Vermont, New Mexico, Hawaii, South Dakota, Alaska, North Dakota, New York, Rhode Island, and Massachusetts.

Figure 10. Measures of Plan Spending and Premiums, by State

State	Unadjusted FEP Spending	Projected Plan Spending	Risk-Adjusted Plan Spending	Beneficiary Premium
Alabama	1,996	1,716	1,698	639
Alaska	1,528	1,362	1,558	499
Arizona	1,671	1,527	1,568	509
Arkansas	1,826	1,619	1,652	593
California	1,779	1,576	1,595	536
Colorado	1,714	1,530	1,633	574
Connecticut	1,651	1,520	1,545	486
Delaware	1,955	1,683	1,623	564
District of Columbia	1,703	1,549	1,540	481
Florida	1,862	1,650	1,585	526
Georgia	2,011	1,713	1,682	623
Hawaii	1,604	1,445	1,484	426
Idaho	1,703	1,523	1,642	583
Illinois	1,676	1,527	1,585	526
Indiana	2,034	1,724	1,739	680
Iowa	1,607	1,502	1,572	513
Kansas	1,843	1,619	1,658	599
Kentucky	1,932	1,683	1,660	601
Louisiana	1,967	1,692	1,652	593
Maine	1,640	1,504	1,522	463
Maryland	1,944	1,674	1,643	584
Massachusetts	1,640	1,508	1,508	449
Michigan	1,850	1,619	1,588	529
Minnesota	1,591	1,466	1,591	532
Mississippi	1,937	1,673	1,688	629
Missouri	1,826	1,624	1,643	585
Montana	1,542	1,434	1,572	513
Nebraska	1,691	1,534	1,627	568
Nevada	1,707	1,533	1,564	505
New Hampshire	1,680	1,545	1,578	519
New Jersey	1,795	1,586	1,530	471
New Mexico	1,551	1,444	1,542	483
New York	1,619	1,480	1,434	375
North Carolina	1,930	1,675	1,699	640
North Dakota	1,441	1,398	1,520	461
Ohio	1,853	1,632	1,606	547
Oklahoma	1,996	1,702	1,711	652
Oregon	1,684	1,522	1,618	559
Pennsylvania	1,820	1,607	1,543	484
Rhode Island	1,601	1,509	1,456	398
South Carolina	2,002	1,708	1,668	609
South Dakota	1,475	1,401	1,534	475
Tennessee	1,970	1,682	1,712	653
Texas	1,918	1,656	1,658	599
Utah	1,955	1,686	1,730	671
Vermont	1,614	1,460	1,521	463
Virginia	1,928	1,660	1,650	592
Washington	1,676	1,517	1,587	528
West Virginia	1,997	1,686	1,663	604
Wisconsin	1,544	1,455	1,540	482
Wyoming	1,527	1,425	1,591	533
Average (unweighted)	1,765	1,572	1,602	543

Figure 11. Projected Plan Premiums by State, by Rank Order

Projected Plan Spending, Not Risk Adjusted		Projected Plan Spending, Risk Adjusted	
Alaska	1362	New York	1434
North Dakota	1398	Rhode Island	1456
South Dakota	1401	Hawaii	1484
Wyoming	1425	Massachusetts	1508
Montana	1434	North Dakota	1520
New Mexico	1444	Vermont	1521
Hawaii	1445	Maine	1522
Wisconsin	1455	New Jersey	1530
Vermont	1460	South Dakota	1534
Minnesota	1466	District of Columbia	1540
New York	1480	Wisconsin	1540
Iowa	1502	New Mexico	1542
Maine	1504	Pennsylvania	1543
Massachusetts	1508	Connecticut	1545
Rhode Island	1509	Alaska	1558
Washington	1517	Nevada	1564
Connecticut	1520	Arizona	1568
Oregon	1522	Montana	1572
Idaho	1523	Iowa	1572
Arizona	1527	New Hampshire	1578
Illinois	1527	Florida	1585
Colorado	1530	Illinois	1585
Nevada	1533	Washington	1587
Nebraska	1534	Michigan	1588
New Hampshire	1545	Minnesota	1591
District of Columbia	1549	Wyoming	1591
California	1576	California	1595
New Jersey	1586	Ohio	1606
Pennsylvania	1607	Oregon	1618
Arkansas	1619	Delaware	1623
Kansas	1619	Nebraska	1627
Michigan	1619	Colorado	1633
Missouri	1624	Idaho	1642
Ohio	1632	Maryland	1643
Florida	1650	Missouri	1643
Texas	1656	Virginia	1650
Virginia	1660	Arkansas	1652
Mississippi	1673	Louisiana	1652
Maryland	1674	Texas	1658
North Carolina	1675	Kansas	1658
Tennessee	1682	Kentucky	1660
Delaware	1683	West Virginia	1663
Kentucky	1683	South Carolina	1668
West Virginia	1686	Georgia	1682
Utah	1686	Mississippi	1688
Louisiana	1692	Alabama	1698
Oklahoma	1702	North Carolina	1699
South Carolina	1708	Oklahoma	1711
Georgia	1713	Tennessee	1712
Alabama	1716	Utah	1730
Indiana	1724	Indiana	1739

Regional Patterns

Looking at states grouped by the ten HHS regions brings out some regional patterns in the variation among states (Figure 12). In many regions, states are all either above the national median or below the national median, and they often show similar changes as a result of risk adjustment.

The eight states in Regions 1 and 2 (the northeast) almost all had spending near or below the median both before and after risk adjustment. New Jersey, New York, and Rhode Island show even lower spending after risk adjustment. All of the states in these regions fall in the rank ordering of states after risk adjustment; New York and Rhode Island become the two lowest-spending states.

With the exception of California and Utah, the states in regions 8, 9, and 10 (western states) had spending below the median before risk adjustment. Projected spending is higher in all of these states after risk adjustment. While most states in these regions remain below the median, Colorado, Utah, Idaho, and Oregon are above the median after risk adjustment. Several states in Regions 8 (the plains and mountain states) and 10 (the Pacific Northwest and Alaska) have particularly large increases in projected spending as a result of risk adjustment.

Region 5 (midwest), 6 (mid-south and southwest), and 7 (midwest) are split. Some states in these regions behave like the western states. Illinois, Minnesota and Wisconsin (region 5), New Mexico (region 6), and Iowa (region 7) all have low spending, with a relatively large increase in projected spending as a result of the risk adjuster, but still remaining below the median of all states. Most of the rest of the states in regions 5, 6, and 7 start out with unadjusted spending above the median. Risk adjustment makes relatively small changes in their projected spending, resulting in spending that remains at or above the median.

Region 3 (the mid-Atlantic) tends to have spending above the median before and after risk adjustment. The exceptions are the District of Columbia and Pennsylvania, which have spending below the national median after risk adjustment. In this region, the risk adjuster lowers spending in all states and the District.

Region 4 (the southeast) is the highest-spending region, both before and after risk adjustment. The eight Region 4 states are all in the top 20 most expensive states before risk adjustment. Only Florida falls below the median after risk adjustment.

Figure 12. Projected Spending in 2006 by HHS Region (Lowest Region to Highest in Risk Adjusted Spending)

State	Not Risk Adjusted	Risk Adjusted	% Change Due to Risk Adjustment
National average	1613	1613	
National median	1547	1596	
New Jersey	1586	1530	-3.5%
New York	1480	1434	-3.1%
Average, Region 2	*1533*	*1482*	*-3.3%*
Connecticut	1520	1545	1.6%
Maine	1504	1522	1.2%
Massachusetts	1508	1508	0.0%
New Hampshire	1545	1578	2.1%
Rhode Island	1509	1456	-3.5%
Vermont	1460	1521	4.2%
Average, Region 1	*1508*	*1522*	*0.9%*
Arizona	1527	1568	2.6%
California	1576	1595	1.2%
Hawaii	1445	1484	2.7%
Nevada	1533	1564	2.0%
Average, Region 9	*1520*	*1553*	*2.1%*
Colorado	1530	1633	6.7%
Montana	1434	1572	9.6%
North Dakota	1398	1520	8.7%
South Dakota	1401	1534	9.5%
Utah	1686	1730	2.6%
Wyoming	1425	1591	11.7%
Average, Region 8	*1479*	*1597*	*8.1%*
Alaska	1362	1558	14.4%
Idaho	1523	1642	7.8%
Oregon	1522	1618	6.3%
Washington	1517	1587	4.6%
Average, Region 10	*1481*	*1601*	*8.3%*
Illinois	1527	1585	3.8%
Indiana	1724	1739	0.9%
Michigan	1619	1588	-1.9%
Minnesota	1466	1591	8.5%
Ohio	1632	1606	-1.6%
Wisconsin	1455	1540	5.9%
Average, Region 5	*1571*	*1608*	*2.6%*

Delaware	1683	1623	-3.6%
District of Columbia	1549	1540	-0.6%
Maryland	1674	1643	-1.8%
Pennsylvania	1607	1543	-4.0%
Virginia	1660	1650	-0.6%
West Virginia	1686	1663	-1.4%
Average, Region 3	*1643*	*1610*	*-2.0%*
Iowa	1502	1572	4.7%
Kansas	1619	1658	2.4%
Missouri	1624	1643	1.2%
Nebraska	1534	1627	6.1%
Average, Region 7	*1570*	*1625*	*3.6%*
Arkansas	1619	1652	2.0%
Louisiana	1692	1652	-2.3%
New Mexico	1444	1542	6.8%
Oklahoma	1702	1711	0.5%
Texas	1656	1658	0.1%
Average, Region 6	*1623*	*1643*	*1.4%*
Alabama	1716	1698	-1.0%
Florida	1650	1585	-4.0%
Georgia	1713	1682	-1.9%
Kentucky	1683	1660	-1.4%
Mississippi	1673	1688	0.9%
North Carolina	1675	1699	1.4%
South Carolina	1708	1668	-2.3%
Tennessee	1682	1712	1.8%
Average, Region 4	*1688*	*1674*	*-0.8%*

Comparisons to Other Data

We looked at published data from two pharmacy benefit managers (PBMs) – Express Scripts (ES) and Medco Health – as well as at other measures of utilization from the FEP data, as published by CMS.[31] There are several limits to the data available for this analysis, but they provide some additional insight into patterns of geographic variation. Specifically, there are differences in dates and the measures reported, as well as missing values for some smaller states. In addition, Medco and Express Scripts have summarized their data and provide information about each state only on a 4- or 5-point scale (i.e., very high, high, low, and very low).

All sources of data consulted reveal substantial spending variation at the state level. There are remarkable inconsistencies, however, across sources. We calculated simple correlations between the different measures, as shown in Figure 13. While there is a fair amount of correlation between the Express Scripts measures and the FEP data, there is far less correlation between Medco's data and the other two sources. The weakest relationship is

[31] Motheral et al., Express Scripts Prescription Drug Atlas; Medco Health, Drug Trend Report 6(1), May 2004.

between Medco's measure of therapy days and the number of prescriptions as measured by Express Scripts. These variables tap different aspects of drug usage. But since they both are measures of the intensity of drug use, the weak correlation is unexpected. These differences warrant further exploration to determine the representativeness of each data set.

Figure 13. Correlation between Federal Employees Plan, Express Scripts, and Medco Data

	Number of prescriptions, 2000 (ES)	Therapy days (Medco)
Unadjusted projected premiums, 2006 (FEP)	0.64	0.27
Number of prescriptions, 2002 (FEP)	0.63	0.44
Therapy days, 2002 (FEP)	0.67	0.39
Number of prescriptions, 2000 (ES)		0.16

In addition to overall drug use patterns, the Express Scripts study reported on the state-by-state prevalence of drug use for 24 separate classes of drugs. Like the overall prevalence of drug use, the data were reported on a 5-point scale. Correlations were examined between the overall prevalence and the prevalence for each category of drugs (Figure 14). The highest correlation was with penicillin use (0.75), and the lowest correlations were with two hormone replacement drugs: estrogen (0.19) and thyroid (0.17). Most of the correlations between use of drugs from individual classes and overall use are between 0.40 and 0.50, which seems to show a surprising absence of consistent patterns from one type of drug to another.

Figure 14. Correlation between Use of Individual Drug Classes and Overall Prevalence, Express Scripts Data, 2000

Drug Class	Premium
Penicillin	0.75
Antihyperlipidemic	0.63
Antidepressant	0.62
Antirheumatic	0.60
Decongestant	0.52
Gastrointestinal	0.50
Cardiovascular	0.49
Anticonvulsant	0.47
Cephalosporin	0.47
Macrolide	0.46
Cough/Cold/Allergy	0.43
Antihistamine	0.42
Diuretic	0.42
Corticosteriod	0.40
Narcotic Analgesic	0.40
Antianxiety	0.37
Antihypertensive	0.35
Calcium Channel Blocker	0.34
Ophthalmic	0.32
Beta Blocker	0.31
Antidiabetic	0.31
Antiasthmatic	0.27
Estrogen	0.19
Thyroid	0.17

There are considerably higher correlations, however, between some similar drugs. Use of cardiovascular drugs, anti-hypertension drugs, calcium channel blockers, and diuretics are all correlated at the level of 0.80 or higher. Since the latter two classes are a subset of the anti-hypertension drugs, which are in turn a subset of cardiovascular drugs, these relationships are not unexpected. On the other hand, beta blockers (also a treatment for hypertension) and drugs taken for high cholesterol (typically used by many cardiac patients) are not correlated at these higher levels. Similarly, some drugs taken for respiratory tract conditions are correlated at higher levels, but others in that group are not. And use of three different classes of anti-bacterial drugs are correlated at levels no higher than 0.60.

These results suggest considerable complexity in the geographic patterns of drug use. Further research with better data sources (or at least more completely reported data) is needed to understand these patterns more fully.

Correlates of Drug Spending

We tested a wide range of possible explanatory variables for the variations in projected plan spending, both before and after risk adjustment. For each, we compared the mean of the variable in the top 15 states to the mean in the bottom 15 states. The results of these tests are shown in Figures 15 and 16.

Figure 15. Differences Between Low-Spending and High-Spending States, After Risk Adjustment

Factor	Mean for the 15 states with the lowest spending	Mean for the 15 states with the highest spending	t Stat	P(T<=t) two-tail
Projected spending per beneficiary in 2006, Not Risk Adj.***	1482	1682	-10.26	0.0000
Projected spending per beneficiary in 2006, Risk Adj.***	1519	1685	-14.19	0.0000
Population Density (# per sq. mile)	938	94	1.39	0.1754
% of people living in a metropolitan area	69.6	63.2	0.83	0.4161
% high school graduate or higher **	86.8	82.6	3.54	0.0014
% bachelor's degree or higher**	29.1	22.9	3.15	0.0039
Median income**	45536	38450	3.34	0.0024
% reporting good or better health status***	86.4	81.5	4.67	0.0001
% heavy drinkers***	6.6	4.3	5.08	0.0000
% with asthma	12.1	11.4	1.67	0.1066
% with high cholesterol	31.5	33.2	-1.70	0.1004
% with diabetes (not pregnancy related) **	6.7	8.2	-3.47	0.0017
% limited by physical, mental, emotional problems**	17.4	20.2	-2.78	0.0097
% with hypertension**	24.4	28.5	-3.51	0.0015
% Smoke Everyday*	16.3	19.2	-2.47	0.0198
% Former Smokers***	27.1	22.2	5.08	0.0000
% Current Smokers*	21.5	24.3	-2.25	0.0324
% Medicare Enrollees Under Age 65***	13.9	18.3	-3.77	0.0008
% Medicare Enrollees Over Age 85**	12.0	10.0	3.45	0.0018
HMO Penetration Rate *	24.5	13.7	2.70	0.0118
Non-Federal Physicians per 100,000 pop.**	333	223	-3.44	0.0018
Pharmacies per 100,000 population **	19	23	-2.87	0.0078
Pharmacists per 100,000 population	154	127	1.65	0.1093
Median Retail Price per Pill, All Customers	2.25	2.25	0.38	0.7056
Median Retail Price per Pill, Third-Party Cust.	2.37	2.36	0.45	0.6536
Median Retail Price per Pill, Cash Customers **	2.27	2.14	3.61	0.0012

* Significant at the .05 level
** Significant at the .01 level
***Significant at the .001 level
Sources listed in Appendix in Figure A-4.

Figure 16. Differences Between Low-Spending and High-Spending States, Before and After Risk Adjustment

Factor	Difference between means in 15 lowest-spending states and 15 highest-spending states (high spending minus low spending)	
	Projected spending, Not risk adjusted	Projected spending, risk adjusted
Projected Plan Payment in 2006, Not Risk Adj.	238***	200***
Projected Plan Payment in 2006, Risk Adj.	151***	166***
Population Density (# per sq. mile)	-26	-844
% of people living in a metropolitan area	10.9	-6.5
% high school graduate or higher	-4.1**	-4.2**
% bachelor's degree or higher	-2.0	-6.2**
Median income	-2767	-7086**
% reporting good or better health status	-4.5***	-5.0***
% heavy drinkers	-2.0***	-2.2***
% with asthma	-0.2	-0.6
% with high cholesterol	2.0*	1.7
% with diabetes (not pregnancy related)	1.9***	1.5**
% limited by physical, mental, emotional problems	1.9	2.8**
% with hypertension	4.6***	4.0**
% Smoke Everyday	2.4*	2.9*
% Former Smokers	-4.6***	-4.8***
% Current Smokers	2.5	2.8*
% Medicare Enrollees Under Age 65	4.3**	4.1***
% Medicare Enrollees Over Age 85	-2.0***	-2.0**
HMO Penetration Rate	-3.3	-10.8*
Non-Federal Physicians per 100,000 pop.	-36	-110**
Pharmacies per 100,000 population	2.8	3.9**
Pharmacists per 100,000 population	-19	-28
Median Retail Price per Pill, All Customers	-0.018	-0.005
Median Retail Price per Pill, Third-Party Customers	-0.016	-0.006
Median Retail Price per Pill, Cash Customers	-0.002	-0.125**

* Significant at the .05 level
** Significant at the .01 level
***Significant at the .001 level
Sources listed in Appendix in Figure A-4.

Although there is a seemingly large difference in the population density of high-spending and low-spending states (94 vs. 938 people per square mile after risk adjustment), this difference is not statistically significant. The proportion of a state's population living in a metropolitan area is also statistically insignificant.

The highest-spending states tend to have a less-educated, lower-income population. After risk adjustment, high-spending states have significantly fewer high school graduates (83% vs. 87%) and college graduates (23% vs. 29%). Median income averages less than $40,000 in high-spending states, but almost $45,000 in low-spending states. These measures are all highly correlated with health status. States with a high proportion of people who report being in good or better health are more likely to have a high proportion of people who graduated from high school (r=.81) and college (r=.60), and have higher median incomes (r=.66).

The goal of the risk adjuster is to account for differences in health status and adjust plan premiums accordingly. However, our analysis shows that at the state level, significant differences in health status remain between low-spending and high-spending states after risk adjustment. High-spending states have a higher proportion of the population with diabetes (8.2% vs. 6.7%) and hypertension (28.5% vs. 24.4%), a higher proportion of the population that smokes (24.3% vs. 21.5%), fewer people who report good or better health status (81.5% vs. 86.4%), and more people who report having limitations because of physical, mental, or emotional problems (20.2% vs. 17.4%). After risk adjustment, differences between the two groups in diabetes, cholesterol, and hypertension are smaller and less significant than they were before the risk adjuster was applied.

Differences between high- and low-spending states actually increase and become more significant for several health-related factors after risk adjustment: the proportion of the population reporting limitations, the percentages who are current or everyday smokers, and the percentage reporting they have ever had asthma. (However, even after this increase, the difference between asthma rates for the two groups of states is not statistically significant.) The difference in overall self-reported health status also grows after risk adjustment. There is a fairly high degree of correlation between many of these health status factors.

Two health-related factors are highly significant, but in an unexpected direction. High-spending states have fewer heavy drinkers (4.3% vs. 6.6%). They also have fewer former smokers (22.2% vs. 27.1%). These two factors are also highly correlated (r=.67).

We also tested the proportion of each state's Medicare population that is under 65 and over 85. Both were highly significant before and after risk adjustment, but in opposite directions. High-spending states have significantly more Medicare enrollees under age 65 (18% vs. 14%), a factor that is negatively correlated with self-reported health status (r=-.70). At the same time, high-spending states have significantly fewer Medicare enrollees over age 85 (10% vs. 12%), a factor that is positively correlated with health status (r=.46).

After risk adjustment, high-spending states had a significantly lower HMO penetration rate (14% vs. 24%). As noted in our discussion of the factors affecting drug prices, this factor is highly correlated with the percentage of a state's population that lives in a metropolitan area (r=.69).

Previous studies of health care utilization have found that areas with a higher number of physicians per capita also tend to have higher spending on health care. We found the opposite to be true for drug spending. After risk adjustment, high-spending states have significantly lower numbers of physicians per capita (223 vs. 333 physicians per 100,000 population). However, the number of drug stores per capita is significantly higher in high-spending states (23 vs. 19 per 100,000 population).

We ran multiple regressions of combinations of these factors. This analysis was complicated by the high level of correlation among so many of the factors. In all of our models in which it was included, health status remained a statistically significant factor. Even after controlling for health status, the number of physicians per capita also remains significant, with an increase in physicians reducing spending.

The Impact of Geographic Variations on Beneficiary Premiums

As described in a previous section, the statutory formula for setting beneficiary premiums requires that beneficiaries pay the additional costs associated with a more expensive plan. Because the law establishes a national benchmark to define the additional costs associated with a more expensive plan, the effect is to make plan enrollees responsible if average costs in a particular region are higher than elsewhere. Enrollees in states where average spending is lower will pay less if plan bids in that state reflect those lower costs.

As shown in Figure 8 and Figure 9, premiums have a broader variation by state than do the other measures of spending. The premiums are perfectly correlated with the risk-adjusted spending, but with a larger spread. Based on this analysis, residents of Indiana would face the highest premiums, 81 percent above those faced by residents of New York, who would pay the lowest premiums. It is important to note that, because the data are based on spending in a single retiree health plan, this analysis is more useful for explaining general patterns than for identifying which states are likely to have higher or lower premiums. For example, it could be that federal retirees living in Indiana share particular characteristics that drive their costs higher, while federal retirees living in New York lack those characteristics. It is possible that spending patterns for all Medicare beneficiaries vary less by geography than do federal retirees, but it is more likely that different states could fall at the extremes of the distribution.

According to this analysis, plan enrollees in about half the states would pay premiums that are at least 10 percent above or below the average of the 50 states. At the extremes, enrollees in seven states would face premiums that are at least 20 percent higher or lower than the average.

A regional analysis would fall along exactly the same lines (but with a wider spread around the average) as the regional analysis of risk-adjusted spending in an earlier section of the report. Thus, projected premiums are highest in southern states and lowest in states on the east and west coasts. Beneficiaries in the South may be charged higher premiums due to regional differences in utilization or other factors that are not explained by the risk adjusters. Because utilization patterns do appear to be regional, a greater use of multi-state regions for Part D would not particularly help to alleviate these premium differences.

Policy Considerations and Areas for Further Research on Geographic Utilization Differences

The clear conclusion from our analysis of geographic variation in utilization is that the variation is not minimal. In reaching this conclusion, we have considered unadjusted spending for the retiree population covered through the Blue Cross/Blue Shield health plan for federal retirees as well as adjusting those spending numbers to project spending under the Medicare Part D benefit package and applying the risk adjusters that will be used in the first year of the Medicare benefit. Although these adjustments reduce the range of variation, they do not eliminate it. Similar analyses conducted by two large pharmacy benefit managers on prescription drug utilization for the general population also identified substantial state-by-state variation.

Our analysis of projected Part D plan premiums shows how the state-level variations could have a real impact on the cost of the new benefit to Medicare beneficiaries, depending on where they live. This finding has potentially serious political implications and reinforces the importance of this line of study. It also triggers the need to identify and consider policy options that might reduce or eliminate these premium differences.

Even though these results appear reasonably robust, future research is needed to understand more fully the patterns of variation. Our analysis of drug spending could by affected by the prices charged for drugs, but we suspect price is a minor factor for two reasons. One is the absence of geographic price variation in the analysis reported in an earlier section of this report. The other is the fact that the FEP data are from a single national health plan, where price variation should be minimized. Nevertheless, more could be learned by exploring further drug utilization without the effect of drug prices. Such analysis is made more difficult because of the challenges in standardizing units of drug use.

Other research could explore the variations in utilization across different therapeutic categories. The analysis of commercial data, reported above, suggests that geographic variation occurs in many different categories of drugs, but that the patterns are not the same across categories. These results strongly call for further investigation. It would be important to understand whether these variations arise because of geographic differences in disease prevalence or because of the prescribing patterns of health professionals trained and practicing in different regions.

Although risk adjustment seems to reduce the amount of geographic variation, it falls far short of eliminating that variation. There is some suggestion from the analysis of correlates of spending that some aspects of health status remain as a source of variation. This suggests there may be additional health status factors that could be added to the risk adjustment system to improve its accuracy. More research is needed to confirm and strengthen this finding and then to identify ways to improve the risk adjusters.

Some supply and health system factors seem to influence use of drugs, since higher use or spending is related to the presence of more drug stores and fewer HMOs. But the relationship of higher drug use to fewer physicians per capita is an anomaly. To the extent

that factors like these in fact influence geographic patterns of drug spending, policymakers will face a choice of whether to leave these variations in the premiums that beneficiaries face or to make adjustments. By one argument, differences can be addressed by the market by creating incentives to the plans to reduce excess utilization. By another argument, they are uncontrollable factors and beneficiaries should be insulated from their effect.

TASK 3 – INTERACTION OF RISK ADJUSTMENT, REINSURANCE, AND RISK CORRIDORS

Introduction

The Medicare drug benefit includes three separate mechanisms to limit the financial risks of prescription drug plans (PDPs). First, systematic and predictable risk differences will be accounted for by risk adjustment. A plan's risk-adjusted premium will vary based on the demographics and diagnoses of its enrollees. Selected diagnoses (for example, heart failure or diabetes) will trigger higher payments, based on the higher average drug spending for persons with those diagnoses. Second, catastrophic or outlier costs will largely be paid through reinsurance. The Federal government will directly reimburse the plan for 80 percent of any individual's drug costs beyond a total spending threshold of $5,100 (for most beneficiaries). Finally, bottom-line profit and loss on total drug costs will be limited by risk corridors. For whatever reason, if the plan's actual drug costs differ significantly from the amount it expected to spend when it established its bid, the Federal government will share a substantial portion of that difference, limiting the financial impact.

These risk protections are important because Medicare PDPs may face substantial, hard-to-quantify risks. First, this is a new benefit, so there is relatively little information available to guide plans' premium-setting decisions in the initial years. Second, unlike typical private-sector drug coverage, this is a stand-alone, individual-purchase benefit, with most individuals choosing annually among competing plans. Plans' experiences with private-sector drug coverage may provide little guidance about the likely degree of risk selection and enrollee turnover in Medicare PDPs. Finally, this is a complex benefit and a complex market. The drug benefit has multiple coinsurance ranges, different coinsurance amounts for poor and non-poor beneficiaries, and other factors making it difficult to project expenditures. At the same time, beneficiaries will be receiving coverage through a combination of PDPs, employer-sponsored plans, and MA plans, while the entire Medicaid-covered population will move from their existing coverage to PDPs as a consequence of the MMA drug benefit.

This section of the report examines two aspects of these risk-limiting mechanisms (risk adjustment, reinsurance, and risk corridors). First, it provides analysis of the MMA language itself: How does the MMA say these factors are to be implemented? Are there any unforeseen interactions among these pieces (or with other parts of the MMA)? Do these risk-limiting mechanisms create opportunities for plans to "game the system"? Second, it analyzes the effectiveness of these factors in limiting plans' financial risks. This second question is answered through a detailed actuarial model of the MMA benefit that includes all three risk-limiting mechanisms.

The MMA Language on Limiting Plans' Risks

This section of the chapter describes the calculation of plan bids and payments for full risk prescription drug plans offering the basic benefit. (These terms are explained below). It does not address the bids and payments for plans not accepting full risk, Medicare Advantage plans, or private employer-sponsored plans. The section first defines the key terms that will be used throughout, then goes through the MMA language determining how bids and payment rates will be determined.

Definitions of Terms

Basic prescription drug coverage or basic benefit is defined in the MMA in terms of deductible and coinsurance levels. The MMA basic benefit has a $250 deductible, 25% coinsurance through $2250 total spending, 5% (or similar) beneficiary coinsurance above the out-of-pocket limit ($5,100 in total spending, for most beneficiaries). There is 80% federal reinsurance of plans' drug payments above that out-of-pocket limit. From the plan's point of view, under the basic benefit, the plan pays nothing for the first $250 in spending, pays 75 percent of costs from there to $2250 in total spending, pays nothing from there to the out-of-pocket limit ($5,100 in total spending for most beneficiaries), and pays a net 15 percent of total costs above the out-of-pocket limit.

Deleted: above that

Plans actuarially equivalent to the basic benefit are treated just like the basic benefit itself. CMS will judge whether or not a plan offering a different combination of deductible, coinsurance, formulary, or other elements is actuarially equivalent to the basic benefit. Actuarially equivalent means that the expected value of the plan's coverage is the same as the expected value of the basic benefit. For purposes of this discussion of the MMA, any benefit package actuarially equivalent to the basic benefit can be discussed as if it were the basic benefit package. So, the term basic benefit used below is either literally the benefit described in the MMA, or a benefit that is judged to be actuarially equivalent to (offers the same expected value of coverage as) the basic benefit. While plans may adjust coinsurance, deductible, formulary, or other aspects of the benefit to achieve an actuarially-equivalent plan, they cannot change the out-of-pocket limit.

Supplemental coverage or supplemental benefit is coverage in excess of the basic benefit. Plans cannot offer less than the basic benefit (or actuarial equivalent), but are free to offer more. Supplemental coverage might take the form of lower coinsurance or deductible. The important aspects of supplemental coverage are as follows: The entire cost of supplemental coverage is paid by the beneficiary (no Federal subsidy). None of the MMA risk-limiting elements apply to the supplemental benefit costs. And, to the extent that a beneficiary has supplemental benefits, the beneficiary must incur more total spending before reaching the out-of-pocket threshold above which reinsurance starts, because the supplemental benefits reduce true out-of-pocket costs. (Hence, supplemental benefits reduce the reinsurance subsidy to a plan.)

Standardized bid amount is the bid for the basic benefit only. If a plan offers a supplemental benefit, then it must pro-rate its bid and show what portion of the bid is for the basic benefit. The federal premium amounts are based solely on the standardized bids. (Any supplemental benefits are paid entirely by the beneficiaries or others, not by the Federal government.) As discussed below, the standardized bid is for a standardized population. That is, plans must bid for a beneficiary population of average risk. The bid is later adjusted based on the actual risk status of plan enrollees.

Direct subsidy is the federal premium contribution for all beneficiaries. That is, when the MMA discusses the direct subsidy, it is talking about Federal payment of PDP premiums. The **reinsurance subsidy** is the federal payment of 80 percent of allowable reinsurance costs, that is, drug costs beyond the beneficiary's out-of-pocket threshold amount. The only dollars that count toward the out-of-pocket threshold are those actually paid by the beneficiary (or by Medicaid or by the Federal low-income subsidy). A beneficiary with no supplemental insurance will hit the out-of-pocket threshold at $5,100 in total drug costs. Those with supplemental coverage, by contrast, will have to incur more total drug costs before their true out-of-pocket payments are high enough to trigger the reinsurance subsidy. Finally, relevant to this discussion, the **low income subsidy** has two parts: a premium subsidy (the Federal government pays all or a portion of the beneficiary's premium, beyond the direct subsidy amount) and deductible/coinsurance subsidy (the Federal government reimburses the plan for all or a portion of the deductible or coinsurance amounts that a beneficiary would otherwise have to pay).

Base beneficiary premium is the average beneficiary premium amount based on the average of all plan standardized bids and the expected average level of reinsurance subsidy. There is one, national, base beneficiary premium in any year. The base beneficiary premium will cover 25.5 percent of expected total costs that are paid through the plans (including reinsurance, but excluding low-income subsidy costs).

Monthly beneficiary premium starts from the base beneficiary premium amount, then adds or subtracts depending on which plan the beneficiary chooses. This is the base beneficiary premium, plus two more parts: a) the full difference between the plan's standardized bid and the national average standardized bid (that is, the beneficiary pays the full amount by which the plan bid exceeds the average, and gains the full amount by which it falls short of the average); and b) any portion of the plan bid attributed to supplemental benefits (that is, the beneficiary pays for all of the supplemental benefits).

Brief Summary of Bid and Payment

To generate a bid, each plan should begin by assuming no risk selection, estimating drug spending based on the national average risk mix. Plan bids should reflect local price and volume norms (average price and prescription patterns in the plan's area) applied to the national average beneficiary mix.

To make a standardized bid, the plan has to project four amounts. First, it must project the costs it expects to incur under the basic benefit (the "standardized bid"), including costs that will be reimbursed via reinsurance. Then, separately, it must project its reinsurance payments. Third, if it offers supplemental benefits, it must calculate the cost of those

benefits (in excess of the standard benefit) separately. Finally, the plan has to estimate its administrative costs (the costs other than the costs of the drugs and associated dispensing fee.) The standardized bid is then the predicted cost of the basic benefit, less projected reinsurance payments, plus administrative costs.

The plan does *not* expect to be paid the amount that it bids. Instead, roughly speaking, it expects to collect its bid times a risk adjustment factor reflecting average risk of its enrollees. (This may then be further modified by the risk corridors.) This is completely different from the bid-and-payment mechanism for MA plans, where plans expect to get the amount that they bid. PDPs, by contrast, will have to project their own risk factors in order to produce a bid that guarantees them a specified amount of money. In other words, a PDP that wants to collect a targeted premium amount must "back-solve" for the impact of the risk adjuster. Even then, because enrollee risk is only known after enrollment, the plan faces uncertainty on the amount of money it will actually collect, for a given submitted bid.

Based on these bids, the beneficiary's monthly premium is the sum of three factors. First, the base (nationally uniform) beneficiary premium is set equal to 25.5 percent of the total projected plan-covered cost (plan premiums plus projected reinsurance payments). Then, the beneficiary pays the full amount by which a plan's bid exceeds the average, after adjustments (described in detail below). Finally, the beneficiary monthly premium includes all costs of supplemental benefits (benefits in excess of the basic benefit).

The federal direct subsidy (premium contribution) for a plan adjusts to ensure that the total payment to a plan matches the intended level. So, the sum of the beneficiary monthly payment and the federal premium subsidy will equal the plan's standardized bid (times a risk adjustment factor) plus the value of supplemental benefits (with no risk adjustment factor). For example, if a plan offering the basic benefit attracts beneficiaries with an average risk factor of 1.1 (ten percent above average), it will receive total premium payments (from beneficiary and government) equal to 110 percent of its bid. The beneficiary pays no part of that extra ten percent. The adjustment is done entirely through the federal contribution. In this example, the Federal contribution is literally calculated as 110 percent of the plan bid, less the beneficiary premium.

Low-income *premium* subsidy will substitute federal dollars for beneficiary dollars in the premium payments, but will leave total payment to the plan unchanged. So, for a given total premium payment due the plan, the low income premium subsidy just shifts the payer from beneficiary to the Federal government. Low-income *deductible and coinsurance* subsidy is best described as a cost-based pass through. Plans will report the total amounts actually paid (beyond the basic benefit) on behalf of low-income enrollees, and the federal government will reimburse plans for that.

At the end of the year, the risk corridor payments become a factor if total actual drug costs that were incurred by the plan (for the basic benefit, excluding administrative costs, and excluding costs that were already repaid to the plan via the reinsurance subsidy or low-income subsidy) fall outside a range centered around the plan's risk-adjusted standardized bid (excluding administrative costs). So, if the plan's actual costs for the drugs differ from the level predicted when the bid was made, there is some sharing of the difference between the plan and the Federal government. On paper, the calculation of costs for the risk

corridors appears different from the cost calculation for the bid, because total costs are initially calculated including low-income deductible and coinsurance subsidy amounts, then low-income subsidy amounts are netted out of the cost calculation. In practice, except for some possible issues with the language of the MMA (discussed at the end of this section), the calculation of the drug costs entering into the bid and the drug costs entering into the risk corridors should be the same.

Detail: Plan Calculation of Bid for Basic Benefit

To offer a bid, the plan must first predict the cost of its benefit package. This is the actuarial value of *all* payments the plan will make *for the standard benefit and any supplemental benefit*. It *includes* the payments that will eventually be repaid through reinsurance. If it offers supplemental benefits, it must apportion the projected costs into costs for the basic benefit and costs for the supplemental benefit.

The most straightforward interpretation of the MMA language is that the actuarial value of the benefit package does *not* include the low-income subsidy payments (for deductible and coinsurance). These are amounts above and beyond its own benefit, that will be repaid by the federal government. Note that the costs the plan projects here (ignoring the low-income subsidy) are therefore nominally different from the costs that are used in the first step of the risk corridor calculation (initially including low-income subsidy costs), but that the risk corridor costs ultimately net out the low-income subsidy costs, making them comparable to the actuarial value used to generate the bid.

Under this reading of the MMA, the cost of low-income subsidy payments is irrelevant at this point, and can be ignored. The plan does not need to project the fraction of enrollees receiving subsidy in order to generate its actuarial value projection. These low-income subsidy costs are a cost pass-through of amounts to be paid beyond the basic benefit, and so do not affect the calculation of the actuarial value of the basic benefit. (There is a secondary effect of induction of demand due to reduced coinsurance under the low-income benefit, but that is addressed in a later section of this chapter). The point here is that the plan's accounting of spending under the plan premium does not have to include any estimate of the actual low-income subsidy payments.

Of that actuarial value, the plan projects the amount of reinsurance payments. Determination of when a beneficiary has exceeded the out-of-pocket maximum is based on actual beneficiary out-of-pocket payments (true out-of-pocket costs), and excludes third-party payments made on the beneficiary's behalf, *except for the following:* Low-income subsidy payments count as if the beneficiary paid them. (So, as above, the direct cost of the low-income subsidy counts as if paid by the beneficiary, and so does not raise the total spending required to meet the out-of-pocket threshold.) Further, Medicaid wraparound counts as if the beneficiary paid those costs. But private supplemental or better-than-standard drug coverage amounts beyond standard benefit do not count as if the beneficiary paid them. So, in principle, a plan needs to know the level of supplemental coverage for its population in order to generate the plan bid, and plans offering supplemental benefits lose some of their reinsurance subsidy.

The plan's bid is then the plan's estimate of four factors, some of which reflect national averages, some local norms. These factors are: the actuarial value of the benefit to be provided by the plan; less the plan's predicted value of the reinsurance subsidy; plus administrative expenses; broken into the cost of the basic benefit (the standardized bid) and any supplemental benefit. All of these are to be based on the national average enrollee, based on information to be provided by the Secretary, so no risk selection is to be assumed when generating a bid. But the plan will calculate an actuarial value for providing the benefit in the plan area. That is, plan bids will reflect the price and prescribing norms in their localities. Bids are therefore an amalgam of the national risk pool, but local price and prescribing norms.

The federal premium contribution, by contrast, may reflect local prices, but will not reflect local prescribing norms or other factors affecting area variation in the volume of drugs per beneficiary. That is, CMS may adjust the Federal premium contribution in an area to reflection variation in drug pricing, but may not make such adjustments to reflect any other factors. If a plan's costs are based on three components – the risk of its enrollees, the prices paid in the area for drugs, and local prescribing norms – beneficiaries in an area are in theory held harmless for the first two factors, but are fully at risk for the third. Beneficiaries in areas where prescription drug use is higher than expected will pay above-average premiums.

There are two additional interesting details regarding the supplemental benefits and the low-income subsidy. First, a literal reading of the MMA suggests an inconsistent treatment of supplemental benefits vis-à-vis risk adjustment. If a plan offers supplemental benefits, the MMA appears to require that the plan price out those supplemental benefits for the national average enrollee mix. That is, the plan's premium for the supplemental benefits, like the premium for the basic benefit, is to be based on the national average enrollee mix and have no allowance for risk selection. But, risk adjustment does not apply to the supplemental benefits portion of the premium. Even if the plan gets significant risk selection, the supplemental premium does not change. This is clearly not a technically correct approach to setting the premium. Ultimately, plans need revenues that match their actual enrolled populations. In practice, one might expect plans to price the supplemental benefit at the expected cost for their expected population, and to ignore the MMA direction to price the premiums (both basic and supplemental) for the national average risk mix.

Second, for the low-income subsidies, the costs projected for the actuarial value exclude any costs that will be passed through to the federal government for the low-income subsidies. This makes the actuarial value here different from the costs calculated for the initial step of the risk corridors (below). For the risk corridor calculation, the low-income subsidy costs are initially included, then specifically removed from the cost calculation. This point is raised because the language describing the risk corridors looks nominally different from the language describing the actuarial value.

Detail: Calculation of Beneficiary Premium for a Plan

The first step in calculation of the beneficiary premium is to determine what the average bid was. That is, CMS must calculate the enrollment-weighted average of standardized plan bids (bids for the standard benefit package), as well as the average projected reinsurance payments. Then, CMS will calculate the base (nationally uniform) beneficiary premium so

that the base beneficiary premium accounts for 25.5 percent of total cost of the benefit including the reinsurance, but excluding the cost of the low-income subsidy.

To get from the (nationally uniform) base beneficiary premium to the premium of an individual plan, various amounts must be added or subtracted. First, CMS will determine how much the plan's standardized bid exceeds or falls short of the enrollment-weighted national average. One adjustment is allowed at this step. The national average may be adjusted to account for geographic variation in drug prices before comparing it to the plan's bid. If CMS believes such an adjustment is warranted, plans in high-priced areas will be compared to the national average premium with an upward adjustment for prices. (And plans in low-priced areas will face a downward adjustment.) Then, any difference between the plan's bid and the (possibly adjusted) average bid is added to the base beneficiary premium. The result is that if a plan bids more than the average, the beneficiary pays that entire additional amount (except possibly for the portion of the difference attributable to local area drug prices.) Finally, if the plan has supplemental benefits, CMS will take the portion of the bid attributable to supplemental benefits and add that to the beneficiary premium. The beneficiary pays the full dollar cost of the supplemental benefits.

The MMA contains no provision that forces the resulting sum to be greater than zero. There appears to be no bar on zero-premium drug plans, and there is no upper limit on premiums. Beneficiaries in a region are completely at risk for regional variation in drug utilization, in the sense of different projected levels of drug utilization for the national average beneficiary risk mix.

Calculation of Payments to the Plan

At this point, all of the bids and premiums have been calculated, and risk adjustment has not directly entered into any calculation. This entire sequence of calculations has been based on the premise that plans will bid for the national average risk mix. Only when it is time to make payments does risk adjustment enter the calculation.

The total premium payment to the plan is just its standardized bid, times a risk adjustment factor. (There is a separate discussion at the end of this section regarding whether CMS should risk-adjust the benefits cost portion of the bid only, or should adjust the total including administrative costs.) Of that amount, the beneficiary pays the monthly beneficiary premium as described above. No risk adjustment enters into that monthly beneficiary premium calculation. The federal direct premium subsidy then makes up the difference between the risk-adjusted standardized bid and the beneficiary monthly premium.

The plan's total plan premium payment, from all sources, is based on the sum of two components. The first component is the total plan standardized bid, risk adjusted. This is paid in part by the beneficiary, with the remainder paid by the Federal government. The second component is the plan's bid for the supplemental benefits, not risk adjusted, paid entirely by the beneficiary. The low-income premium subsidy does not affect the total premium paid, but just shifts the cost of the premium from beneficiaries to the Federal government.

Reinsurance payments make up an additional part of net plan revenue. The plan collects 80 percent of allowable costs beyond the out-of-pocket threshold amount, for each beneficiary. If this amount is actually paid as an interim payment (part of the capitation amount), there must be a reconciliation of the aggregate capitation payments versus the actual amount owed. For beneficiaries with no supplemental coverage, determination of the point at which the beneficiary has met the out-of-pocket threshold is straightforward. For those who may have drug coverage from multiple sources, however, it may be difficult for CMS or the plan to determine when a beneficiary's true out-of-pocket costs have exceeded the out-of-pocket threshold that triggers the reinsurance payments.

Low income deductible and coinsurance subsidy payments, by contrast, add nothing to *net* plan revenue. These payments are just a pass-through. The plan pays these amounts over and above its basic benefit, to cover deductible and coinsurance amounts for the low-income beneficiaries. Then it bills the federal government for the amounts paid. As with the reinsurance amounts, if the plan collects some interim capitation amount for these subsidy payments, there must be an aggregate reconciliation at year-end.

Finally, after the end of the year, a reconciliation of bids and costs will determine whether any risk corridor payments must be made. This is based on a comparison of risk corridor costs and a "target amount", defined below. If the amounts differ substantially, the plan and the Federal government share in that difference.

The risk corridors only take into account the actual costs of the drugs (the benefits costs), not plan overhead amounts. So, the risk corridor costs are the actual cost of drugs--excluding administrative costs--that would have been paid under the basic benefit (that is, excluding supplemental coverage). However, unlike the initial premium calculation, these costs are first calculated including the low-income subsidy (coinsurance and deductible) amounts that exceed the basic benefit. Then, these low-income subsidy costs are subtracted out of gross plan drug payments, along with any reinsurance amounts the plan has received. The result – gross plan drug outlays, less amounts already paid back to the plan by the Federal government – become the risk corridor costs.

At this point, there is a separate technical issue with the MMA language regarding the low-income subsidy amounts. The MMA language for the risk corridors does not distinguish between the deductible/coinsurance amounts from the premium subsidy amounts. This is discussed below.

The risk corridor costs are compared to a target amount – the amount the Federal government expected the plan to spend, based on the plan's bid. This is the risk adjusted standardized bid, excluding administrative expenses. Payments are then made based on the difference between corridor costs and corridor target amount.

Calculation of Low-income Subsidy Payments

Finally, the entire financial picture for plans and beneficiaries also includes substantial low-income subsidy payments. Because the rules governing the payments are somewhat complex, they are described in detail in this section.

The MMA offers additional premium subsidy and reduced deductible and coinsurance amounts for individuals with low incomes who are enrolled in a Medicare Advantage prescription drug plan or a Medicare prescription drug plan. The subsidies and benefits described below do not appear to apply with individuals who merely have qualifying drug coverage, such as employer-sponsored coverage.

Beneficiaries with incomes below 135 percent of the poverty level (and meeting maximum asset tests) will have the opportunity to pay zero premium for their plan. The premium subsidy is set at the enrollment-weighted average of all premiums in a market area, with a guarantee that at least one plan will be available as a zero-premium plan for low-income individuals. The law does not appear to prevent a low-income person from purchasing a more expensive plan if desired. It only caps the maximum premium subsidy at the level of the average plan in the market.

Between 135 and 150 percent of poverty, there is a sliding-scale premium subsidy, so that beneficiaries at 135 percent of poverty pay zero premium (assuming they choose a plan whose premium is at or below the average in their market), while those above 150 percent of poverty pay the full premium.

The deductible and coinsurance amounts also vary as described below. In each case, there is no "doughnut hole" in the coverage, and instead there is a reduced coinsurance amount that is paid all the way up to the out-of-pocket threshold:

- Institutionalized dual-eligible beneficiaries with income below 135 percent of poverty have completely free drug coverage. They pay no deductible and no coinsurance.
- Next, other dual-eligible beneficiaries with incomes up to 100 percent of poverty have no deductible, pay a $1/$3 copay (generic/non-generic) up to the out-of-pocket limit, and have no coinsurance beyond that limit.
- Beyond that, other individuals with incomes up to 135% of poverty pay no deductible, and pay the greater of a 5% coinsurance or a $2/$5 copay, with no cost sharing beyond the out-of-pocket threshold.
- Finally, individuals between 135 and 150 percent of poverty pay a $50 deductible, and have a 15 percent coinsurance up to the out-of-pocket threshold.

Some Potential Issues with the MMA Language on Bid, Payment, and Subsidy for PDPs

This section outlines several potential policy issues from the MMA language itself, from opportunities for potential "gaming of the system" and from possible effects of the low-income subsidies. Each issue has a separate brief discussion.

Treatment of Low-income Subsidy Payments in the Risk Corridor Calculation

In calculating the risk corridor payments, the MMA first says to count all costs incurred by the plan under the basic benefit, including costs eventually repaid by reinsurance, and including costs incurred because of mandated reductions in deductible and coinsurance

liabilities for low-income beneficiaries. Then, the reinsurance payments and the low-income payments are taken out of this cost basis, before comparing to the risk corridor target amounts.

The language issue is that this section of the statute (1860D-15 (e)(1)) refers to the low-income subsidy as monies paid under 1860D-14, which includes not just the deductible/coinsurance subsidies but also the premium subsidy. While it is correct to net out the deductible/coinsurance subsidies (because those amounts were included in the cost computation for the risk corridors), it would not be correct to include the low-income premium subsidy amounts. The premium subsidies do not affect the total amount of money going to a plan, but merely determine who pays the beneficiary portion of premiums (beneficiaries or taxpayers). To calculate the risk corridors correctly, you need to interpret that as meaning all subsidies that resulted in additional payments to the plan based on the beneficiary's poverty status (the deductible/coinsurance subsidy), not all subsidies including the premium subsidy.

Treatment of Overhead Costs in the Risk Adjustment Process as it Relates to the Risk Corridors

The MMA language is not completely clear on how overhead costs are to be treated in the risk adjustment. One part of the statutory language says to risk adjust "the bid" (which includes the administrative costs), while another says to subtract out "the administrative costs" for calculation of the risk corridors, which would then *not* be risk adjusted. This could lead to a technical problem in the calculation of the risk corridors.

This is probably best explained by a simple numerical example. Suppose a plan's total bid is $1000, consisting of $100 in overhead and $900 in projected drug costs. Suppose further that the plan attracts extremely sick individuals so that the average risk factor is 2.0. What should this plan's risk corridor target be?

The most reasonable reading of the intent of the law would give an answer of $1,800. The risk corridors are based on drug costs only. The plan expected to spend $900 on the average beneficiary, it actually attracted beneficiaries with twice the average risk, therefore it should be expected to spend $1,800.

A literal reading of the law, by contrast, might yield a target amount of $1,900, if the entire bid is risk adjusted. That is, the MMA literally says to take the risk adjusted plan bid ($2000), and subtract overhead costs ($100), to arrive at the target ($1,900).

Empirically, this should be a relatively small factor for most plans. The discrepancy between the correct amount ($1,800 above) and the "literal reading" amount will be due to the interaction of the overhead times the risk adjustment factor. Both of these amounts, for the typical plan, should be small. Technically, CMS could arrive at the correct amounts if it treated plan overhead consistently with respect to risk adjustment. CMS could risk adjust only the non-overhead portion of payments, and calculate the target amounts literally by the MMA language, and arrive at the correct amount. (In the example, the risk-adjusted bid becomes $100 + ($900x2) = 1900, risk adjusted bid less overhead is $1,900 – 100 = $1,800.) Or it could risk-adjust the entire bid, and subtract off a risk-adjusted overhead amount in the

target calculation. (In the example above, the risk-adjusted bid becomes $1000x2 = $2000, the target becomes $2000 – ($100x2) = $1,800). The MMA language becomes internally inconsistent only if overhead is treated one way for determining plan payments (that is, overhead is included when determining the risk-adjusted plan bid) but treated differently for determining the risk corridor target (that is, overhead is not risk adjusted when subtracted from the risk-adjusted plan bid).

No Risk Adjustment of Supplemental Benefit Amounts

The plan must submit a total bid based on the national average beneficiary risk mix. This includes its bid for supplemental benefits. Based on that bid, the beneficiary pays an amount for supplemental benefits based on the expected costs of supplemental benefits for the average risk mix. The federal government makes no payments for the supplemental benefits.

The net result is that risk adjustment is never applied to the plan payments covering the cost of the supplemental benefits. Thus if a plan follows the letter of the law and accurately bids for the national average risk mix, and gets a riskier-than-average mix, it will lose money on the supplemental benefits portion of the bid.

It is not clear whether this was an oversight or an intentional disincentive to offer supplemental benefits. Overall, three provisions of the law may discourage the offering of supplemental benefits. First, supplemental benefits reduce the reinsurance subsidy, because only true beneficiary out-of-pocket amounts count toward the out-of-pocket threshold (except for Medicaid and low-income subsidy payments). Second, risk corridors do not apply to the supplemental portion of benefits, so plans are fully at risk for those costs. And finally, plans (in theory) will only receive the expected costs of the supplemental benefits for the average risk mix, and so would expect to incur losses on the supplemental portion of benefits if they attract a riskier-than-average mix.

What Happens to Low-Income Subsidy Payments in a Plan with Supplemental Benefits?

There may be some potential confusion in the way low-income deductible and coinsurance subsidy payments should be counted in a plan with supplemental benefits. One consistent reading of the law is as follows. Under the MMA, low income subsidy should be treated just like a cost-based pass-through payment. To a first approximation, it does not affect the plan's bid or premium, because it is a payment made for what is otherwise covered by the plan. It does not directly affect the actuarial value of the plan (i.e., the bid), though it may have indirect effects due to induction effects (see below).

In that case, the treatment of low-income beneficiaries in plans with supplemental benefits becomes a case to test this reading of the law. Briefly, what do you do with a low-income beneficiary enrolled in a private plan that is more generous than the low-income cost sharing provisions themselves? The correct answer, under this reading of the MMA, is: do nothing until the total benefit runs out, then only pay such subsidies as are necessary to reach the mandated subsidy level beyond the plan-provided benefits. For example, if a plan pays all drug costs, no low-income deductible or coinsurance subsidy payments would be made if a

low-income beneficiary enrolled in that plan. Only when a plan has to exceed the payments it would make under its benefit package, in order to hit the low-income deductible and coinsurance amounts, do those excess payments become part of the low-income subsidy cost-based pass-through payment that CMS pays to the plan.

One more question that tests this reading is the treatment of Medicaid beneficiaries. How do the low-income subsidy amounts work when Medicaid wraps around the plan drug coverage? Medicaid beneficiaries are now going to be enrolled in private drug plans, with Medicaid supplementing the private plan. Under this reading of the MMA, the private plan will pass the low-income subsidy costs through to Medicare. Medicaid will only pay those drug costs beyond the amounts covered by the low-income deductible and coinsurance subsidies.

Incentive for Plans to Load Costs onto Overhead and Under-project Drug Costs

This next section briefly asks whether plans have any obvious incentives to attempt to "game the system" when submitting the bid, based on the MMA rules. The term "game the system" means offering bids that differ significantly from the competitive level, in order to take advantage of the rules established by the MMA. This does not include strategies such as attempting to structure benefit to attract better-than-average risks. This only asks whether plans appear to have an incentive to report an unbiased set of cost and overhead estimates when submitting bids.

Initially, the rules appear to favor strong price competition and lean benefit offerings. Beneficiaries pay dollar-for-dollar for all unexplained variation in plan bids, with no sharing of costs between beneficiary and federal government. Beneficiaries also pay fully for any supplemental benefits, and offering of supplemental benefits reduces the plan's reinsurance subsidy. Both of these should substantially handicap any plan attempting to collect above-market premium rates or above-market depth of benefits.

To analyze openings for "gaming the system", there must be some assumption of adequate competition in each market area. Clearly a plan that is effectively a monopoly has substantial scope for setting an above-market-determined premium. In a competitive market, by contrast, the total plan bid is fairly constrained to be in alignment with competitors' bids. The question to examine here, then, is whether, in a competitive market, plans appear to have anything to gain by mis-reporting the components of the bid (overhead, drug costs, expected reinsurance), keeping the net bid amount fixed.

First, the MMA system appears to provide incentives to shift reported costs onto overhead, away from the drug (benefits) costs. Over-reporting overhead costs in the bid, offset by a lower estimated actuarial value for the drugs themselves, would keep the beneficiary premium at the competitively-determined level, yet result in a lower risk corridor target amount, higher likelihood of "losses" (actual costs exceeding the target), and potentially greater likelihood of recovering risk corridor payments. Unless there is explicit ex post reconciliation of the overhead amount in the bid with an accounting estimate of overhead, a drug plan might consider this strategy. The (downward biased) estimate of drug costs (actuarial value) would then result in greater likelihood of risk corridor payments to the plan, if actual drug costs merely met the (unbiased) predicted level.

This incentive arises from two factors. First, the premium bid includes overhead costs but the risk corridor excludes them. Second, unless CMS intends to audit plans and determine some "true" overhead costs, the plan's projected overhead will be used throughout the calculation. This means that the discrepancy between the total premium and the risk corridor target is based entirely on a figure that the plan projects and is not subject to external verification. Plans have some latitude in choosing the gap they wish to project between total premium and risk corridor target.

It is not clear that plans can or would respond to this incentive by altering their bids to load costs onto overhead. After the initial year of operation, plans must refer to base year drug utilization when developing their bid for the coming year. Plans are also instructed to apply generally accepted accounting practices (GAAP) rules in the allocation of capital and other costs in overhead. These restrictions should limit plans' ability to shift projected premium dollars from the benefits costs to the overhead category. CMS might nevertheless be cautious in accepting any claims of unusual benefits costs savings offset by higher overhead amounts.

Plans do not appear to have any particular incentive to mis-report projected reinsurance payments, except for a modest "cash flow" incentive to receive earlier payments prior to a reconciliation of projected and actual reinsurance amounts. That is, the true level of reinsurance payments will only be known at the end of the year, and CMS may make some interim payments (based on the plans' projection of reinsurance amounts) throughout the year. If so, a higher projection would give the plans cash up front, to be returned after reconciliation of actual and projected amounts.

Beyond that, there does not appear to be any incentive to manipulate the proportion of the bid that is loaded onto projected reinsurance amounts, keeping the beneficiary premium at the competitively-set level. The risk corridor target amount is just the plan standardized bid (risk adjusted). Any tradeoff between projected actuarial value and projected reinsurance that keeps the standardized bid fixed will have no effect on the risk corridor targets. The risk corridor costs are based on actual outlays and actual reinsurance amounts. Thus, the costs counted for reinsurance do not depend on the projections that enter into the plan bid at all. On net, then, if the level of the bid is fixed by competitive pressure, the plan faces no gain from biasing the estimate of reinsurance payments (except the possible short-term cash flow advantages noted above).

Finally, if consumers' actual choices of health insurance do not respond fully and immediately to differentials in premiums and offerings each year, plans may have some modest incentive to game the changing risk corridors.

Some health insurance markets, particularly the market for Medicare supplemental insurance, are characterized by "sticky" choices. Some substantial fraction of consumers appears unwilling to change plans even when faced with fairly substantial premium differentials across plans. Whether or not beneficiaries' choice of drug plans will be "sticky" is an empirical issue. If it is, however, this raises another potential way in which plans might "game the system" by offering bids or bid information that differs from unbiased estimates or from the competitively-determined level.

If beneficiaries seldom change plans, then PDPs may take advantage of the changing risk corridor thresholds to buy market share with low premiums early on, and earn profits from that market share in later years. That is, the risk corridors are symmetric only within a single year. If there is opportunity for plans to trade roughly equal-sized profits and losses across years, they have an incentive to take losses in 2006 and 2007 (where they have good protection from losses) and take profits in 2008 and later (when they share a lower portion of profits back with the federal government). Even if the overall (multi-year) pre-risk-corridor profits and losses cancel, plans will generate net payments from the risk corridor through early losses and late profits.

Whether or not plans would consider taking advantage of this depends on whether they believe they can exploit market share to raise premiums in later years, and, to some extent, whether they believe that their competitors may follow this strategy. Given the likelihood of increasing enrollment in low-premium years and reducing enrollment in high-premium years, plans may be reluctant to try this strategy. That is, they may fear that losses will outweigh gains. That would reduce plans' willingness to attempt such a "loss-leader" pricing strategy.

Incentive to Enroll Low-income Individuals

The treatment of low-income beneficiaries is a quantitatively significant concern for the PDPs. The 2004 Medicare Trustees' Report estimated that about one-third of individuals enrolled in Part D prescription drug plans (that is, excluding employer-sponsored plans) will be eligible for some low-income subsidy. Of the projected 32 million enrollees in 2006, the Trustees report estimates that almost 11 million will have a low-income subsidy. Thus, roughly speaking, a third of persons in the prescription drug plans will have some reduced deductible and coinsurance amounts due to low income. It is reasonable, therefore, to ask whether the MMA implementation will provide any incentives or disincentives for plans to enroll this large, subsidized population.

As described earlier in the document, neither the premium subsidies nor the copayment and deductible subsidies should play a *direct* role in the plan's premium calculation. *For a given level of drug spending* for a person, the plan's net liability for drug costs for a low-income person should be the same as for a non-low-income person.

Concerns might reasonably center around two factors. First, reduced coinsurance for the low-income population should result in "induced demand", that is, systematically higher drug spending for this population. For example, the CMS Actuary assumes that every dollar of additional coinsurance reduction will induce an additional dollar of total drug spending. Under this assumption, beneficiaries with no or reduced cost sharing should be expected to have systematically higher total spending. Plans might therefore consider the low-income population to be a money-losing population unless there is some adjustment in the payment formula to account for the demand inducement effects of the low-income subsidy.

A second and more minor consideration is the plan's administrative cost for these individuals. Plans will be told which individuals qualify for the low-income subsidy. Based on the MMA language, categorization of individuals as low-income will be done via state Medicaid offices. For these individuals, plans must track amounts spent from the subsidy

pool, then apply for and receive reimbursements for those amounts from the Federal government. The added complexity of this system means that administrative costs may be somewhat higher for low-income beneficiaries than for others.

An Actuarial Model of Reinsurance, Risk Adjustment, and Risk Corridors

The final section of this chapter presents a simple actuarial model of the MMA benefit, including reinsurance, risk adjustment, and risk corridors. The point is to demonstrate empirically how reinsurance, risk adjustment, and risk corridors will work together to limit plan financial risk under the MMA drug benefit.

Actuarial Model: Methods

The underlying data source is the Medicare Current Beneficiary Survey (MCBS) Cost and Use files. Files from 1997 to 2001 were pooled together to form the database. Persons had to be in successive years (e.g., in 1997 and 1998) to be included, so that the prospective risk adjustment model could be run for them. For example, 1997 diagnoses from claims data were use to predict 1998 drug spending. Certain categories of beneficiaries had to be excluded. Among these were MA enrollees (with no claims data available from which to draw diagnosis information), nursing home residents (with no drug cost data on the MCBS, only full-year community residents were used), hospice enrollees in the base year (all claims information is lost once a beneficiary enrolls in hospice), and MCBS "ghosts" (persons used to fill gaps in the sample for decedents, whose data cannot be matched across successive years of data.)

Of persons remaining in the sample, total drug spending in each year was inflated to $2500, to approximate projected total drug spending in 2006. The analysis was repeated inflating the totals to $3,000 and to $3,500 to show that the results did not vary appreciably with the change in the average cost.

This was a simple analysis, and no adjustments were made to spending as reported on MCBS, despite large differences in mean spending by drug coverage. That is, there were no detailed adjustments to account for existing coverage differences, merely an across-the-board inflation factor so that mean spending matched $2,500 (or $3,000 or $3,500) mean in each year. No amounts were added to account for plan overhead. This is an analysis of drug costs only and does not include an allowance for overhead in the plan premium.

The results of this model do not exactly match figures published by the CMS Actuary. The Actuary's methods and results were described in detail in the 2004 Medicare Trustees' Report, and in a separate report on Part D methodology. Based on those documents, CMS's approach started from 1998 MCBS drug spending, removed the impact of price discounting, added perhaps 20 percent to totals to account for underreporting, and added an average of 11 percent to account for induction effects due to new drug coverage. The result was an estimated drug spending of $3030 in 2006, followed by an assumed 15 percent savings due

to efficiencies of the PDPs, resulting in a projected direct federal premium subsidy of $905.59, and average reinsurance amount of $399.08.

The simple model used here did not match the cost breakout from the Actuary's more sophisticated model. This should not affect the main conclusions, however, because the results are demonstrated for a wide range of assumed spending. The results (below) on limitation of risk appear robust to/with/for--? several different choices of mean spending.

The actuarial model begins with the inflated drug spending from the MCBS, and models the MMA standard benefit, from the perspective of plan (premium) spending. This includes no payment below the $250 deductible, 75 percent of drug costs up to $2250, no payment from there to $5100, then payment of 95 percent of costs above $5100, offset by the Federal government 80 percent reinsurance. There are no factors for moral hazard based on current or MMA coverage. The model just reshuffles the total fixed drug dollars present on the MCBS file. The net result of this step is, for each beneficiary, an estimated plan spending, reinsurance amount, and beneficiary out-of-pocket spending for drugs.

The next step was to calibrate and apply the CMS drug risk adjuster. Diagnosis information was stripped from claims data using the methods that CMS uses for the risk adjustment (selected physician specialties, selected outpatient and inpatient provider number ranges). The CMS HCC model, as modified for drug risk adjustment, was calibrated on the MCBS sample. Overall goodness of fit (R-squared) was 22 percent. The model was calibrated using the estimated plan liabilities net of reinsurance, and the results were used to generate a risk factor for each person in the sample.

Now that spending and risk factors were determined, the next step was to model plan bid and payments. The PDP was assumed to bid at cost *assuming no risk selection*. That is, the plan was assumed to bid the actuarial value of drug cost for entire MCBS population. The point of the remainder of the exercise is to see what happens to plan profits *when there is risk selection*. That is, how much financial risk do plans face from unexpectedly high or low drug spending.

At this point, the MMA payment rules were applied, including reinsurance above $5,100 in total spending, risk adjustment of federal contribution, and risk corridors around a risk adjusted plan bid, using both the 2006-7 corridor rules and the 2008-9 corridor rules. This exercise assumes that the plan offers the basic drug coverage, and ignores the low-income subsidy. That is, this is basic drug coverage for non-poor enrollees.

The endpoint of the analysis was to tabulate plan profit and loss in several ways. First, show raw profits and losses if there had been no risk-limiting factors whatsoever. (That is, assuming a fixed dollar total of reinsurance money equal to the average, and no risk adjustment or risk corridors. Second, show profits and losses with reinsurance only (using actual reinsurance amounts based on persons assumed to enroll in plan). Third, show profits and losses with both reinsurance and risk adjustment of the Federal plan contribution. Finally, show profits and losses with reinsurance, risk adjustment, and risk corridors (06-07 rules and 08-09 rules).

Finally, this analytical model was run on several biased populations. Most of these "biased groups" model a severe level of risk selection. These should be viewed as providing an extreme, "acid test" examination of the risk-limiting aspects of the MMA, not as providing a reasonable guess about average selection. These included populations defined as follows:

- Level of drug spending (>$500, >$1000, $2000)
- Health status (general health, obesity)
- Diagnoses present in the current (drug spending year) claims.

Actuarial Model: Results

These populations represent very severe assumptions about risk selection. They should not be interpreted as providing likely estimates of actual risk selection and profit and loss. Instead, this analysis shows how strongly the combined effect of reinsurance, risk adjustment, and risk corridors will limit MMA drug plan profits and losses.

In general, the results in the table below can be summarized as follows: Reinsurance appears to cut the raw profits or losses roughly in half, on average, for most of the populations. Risk adjustment then appears to remove about a third of the remaining profit/loss. The risk corridors then cut the remaining profits or losses by roughly two-thirds. The net result is that very large original (raw) profits and losses – those that would obtain with no adjustments – are reduced to about one-seventh of their original level after all three risk-limiting rules have been applied. These results are roughly the same whether a mean spending of $2500 or $3000 or $3500 is assumed (only results from a mean of $2500 are shown).

The only exceptions to the general observation about profits are the cases of extreme risk selection where all the low-cost cases appear in one plan. In that case, the risk protections serve to reduce revenues drastically, but profits remain high because costs are such a small fraction of revenues. Most of the revenue dollars are removed by the risk limiting mechanisms, but profit as a percent of revenue remains high because costs are so low. In practice, even in these cases, the risk limiting mechanisms substantially reduce payments to the plan, relative to a system with no risk adjustments.

Actuarial Model of Plan Profit and Loss for MMA Drug Benefit, Using MCBS Pooled 1997-2001 Data
For Risk Selection Based On Criteria Listed, With Plan Bid Set Actuarially Fair for Entire MCBS Population
(Model uses mean per capita drug spending of $2500)
Creation date 1/17/05

		Total Spending			Reinsurance		Estimated Premium under MMA Rules			Scenarios Showing the Impact of Risk Protections: Estimated Plan Revenue From All Sources					Estimated Plan Profit Or Loss (As % of Total Plan Revenue From All Sources)				
	% of Population	Total Drug Spending	Bene Out-of-Pocket	Through Plan	Reinsurance	Plan Spending net of reinsurance	Total	Federal	Bene.	No Risk Protections	Reinsurance	Reinsurance + risk adjustment	Rreinsurance, risk adjustment, 2006/7 risk corridors	Rreinsurance, risk adjustment, 2008/9 risk corridors	No Risk Protections	Reinsurance	Reinsurance + risk adjustment	Rreinsurance, risk adjustment, 2006/7 risk corridors	Rreinsurance, risk adjustment, 2008/9 risk corridors
Total	100%	$ 2,500	$ 1,212	$ 1,288	$ 332	$ 956	$ 956	$ 627	$ 328	$ 1,288	$1,288	$ 1,288	$ 1,288	$1,288	0%	0%	0%	0%	0%
Drug Spending in Current Year																			
Total drug spend > $500																			
No	24%	$ 147	$ 121	$ 26	$ -	$ 26	$ 691	$ 363	$ 328	$ 1,288	$ 956	$ 691	$ 173	$ 197	98%	97%	96%	85%	87%
Yes	76%	$ 3,242	$ 1,557	$ 1,686	$ 437	$ 1,249	$1,039	$ 711	$ 328	$ 1,288	$1,392	$ 1,476	$ 1,622	$ 1,586	-31%	-21%	-14%	-4%	-6%
Total drug spend > $1000																			
No	36%	$ 345	$ 205	$ 140	$ -	$ 140	$ 745	$ 416	$ 328	$ 1,288	$ 956	$ 745	$ 277	$ 302	89%	85%	81%	49%	54%
Yes	64%	$ 3,701	$ 1,774	$ 1,927	$ 517	$ 1,410	$1,073	$ 745	$ 328	$ 1,288	$1,472	$ 1,590	$ 1,837	$ 1,800	-50%	-31%	-21%	-5%	-7%
Total drug spend > $2000																			
No	56%	$ 750	$ 331	$ 419	$ -	$ 419	$ 817	$ 488	$ 328	$ 1,288	$ 956	$ 817	$ 516	$ 544	67%	56%	49%	19%	23%
Yes	44%	$ 4,706	$ 2,324	$ 2,382	$ 750	$ 1,632	$1,131	$ 802	$ 328	$ 1,288	$1,706	$ 1,881	$ 2,258	$ 2,220	-85%	-40%	-27%	-6%	-7%
Medicaid, Health Status, Obesity																			
Medicaid beneficiary																			
No	86%	$ 2,414	$ 1,181	$ 1,233	$ 294	$ 939	$ 937	$ 608	$ 328	$ 1,288	$1,250	$ 1,231	$ 1,231	$1,231	4%	1%	0%	0%	0%
Yes	14%	$ 3,027	$ 1,407	$ 1,620	$ 565	$ 1,055	$1,072	$ 743	$ 328	$ 1,288	$1,521	$ 1,637	$ 1,637	$1,637	-26%	-7%	1%	1%	1%
Health status fair/poor																			
No	72%	$ 2,094	$ 1,040	$ 1,055	$ 200	$ 855	$ 902	$ 573	$ 328	$ 1,288	$1,156	$ 1,102	$ 1,083	$1,101	18%	9%	4%	3%	4%
Yes	28%	$ 3,525	$ 1,649	$ 1,876	$ 665	$ 1,211	$1,092	$ 764	$ 328	$ 1,288	$1,621	$ 1,757	$ 1,829	$1,792	-46%	-16%	-7%	-3%	-5%
Body Mass Index																			
0:Miss	0%	$ 2,319	$ 1,220	$ 1,099	$ 123	$ 976	$1,052	$ 724	$ 328	$ 1,288	$1,079	$ 1,176	$ 1,137	$1,164	15%	-2%	6%	3%	6%
1:Und	4%	$ 2,083	$ 994	$ 1,089	$ 292	$ 797	$ 862	$ 534	$ 328	$ 1,288	$1,248	$ 1,155	$ 1,120	$1,143	15%	13%	6%	3%	5%
2:Norı	40%	$ 2,209	$ 1,084	$ 1,125	$ 248	$ 877	$ 920	$ 592	$ 328	$ 1,288	$1,203	$ 1,168	$ 1,153	$1,168	13%	6%	4%	2%	4%
3:Ove	36%	$ 2,490	$ 1,203	$ 1,288	$ 327	$ 960	$ 949	$ 621	$ 328	$ 1,288	$1,283	$ 1,276	$ 1,276	$1,276	0%	0%	-1%	-1%	-1%
4:Obe	20%	$ 3,182	$ 1,529	$ 1,653	$ 521	$ 1,132	$1,054	$ 726	$ 328	$ 1,288	$1,477	$ 1,575	$ 1,615	$1,588	-28%	-12%	-5%	-2%	-4%

Diagnoses in the Current Year																				
Rheumatoid arthritis																				
No	95%	$ 2,438	$ 1,181	$ 1,257	$ 317	$ 940	$ 946	$ 617	$ 328	$ 1,288	$1,272	$1,262	$ 1,262	$1,262	2%	1%	0%	0%	0%
Yes	5%	$ 3,783	$ 1,858	$ 1,925	$ 645	$ 1,280	$1,163	$ 835	$ 328	$ 1,288	$1,600	$1,808	$ 1,877	$1,838	-50%	-20%	-6%	-3%	-5%
Asthma																				
No	95%	$ 2,404	$ 1,172	$ 1,232	$ 299	$ 933	$ 941	$ 613	$ 328	$ 1,288	$1,254	$1,240	$ 1,240	$1,240	4%	2%	1%	1%	1%
Yes	5%	$ 4,362	$ 1,999	$ 2,363	$ 973	$ 1,389	$1,238	$ 910	$ 328	$ 1,288	$1,929	$2,211	$ 2,306	$2,264	-84%	-22%	-7%	-2%	-4%
Bipolar and similar mental illness																				
No	97%	$ 2,428	$ 1,182	$ 1,245	$ 306	$ 939	$ 943	$ 614	$ 328	$ 1,288	$1,262	$1,249	$ 1,249	$1,249	3%	1%	0%	0%	0%
Yes	3%	$ 4,636	$ 2,101	$ 2,535	$1,093	$ 1,441	$1,340	$1,012	$ 328	$ 1,288	$2,049	$2,434	$ 2,486	$2,451	-97%	-24%	-4%	-2%	-3%
Multiple Sclerosis																				
No	100%	$ 2,490	$ 1,210	$ 1,280	$ 326	$ 954	$ 954	$ 626	$ 328	$ 1,288	$1,281	$1,280	$ 1,280	$1,280	1%	0%	0%	0%	0%
Yes	0%	$ 4,988	$ 1,741	$ 3,247	$1,827	$ 1,420	$1,279	$ 951	$ 328	$ 1,288	$2,782	$3,106	$ 3,191	$3,148	-152%	-17%	-5%	-2%	-3%
Parkinsons																				
No	99%	$ 2,474	$ 1,200	$ 1,274	$ 324	$ 950	$ 951	$ 623	$ 328	$ 1,288	$1,280	$1,275	$ 1,275	$1,275	1%	0%	0%	0%	0%
Yes	1%	$ 4,460	$ 2,169	$ 2,291	$ 909	$ 1,382	$1,290	$ 962	$ 328	$ 1,288	$1,865	$2,199	$ 2,245	$2,213	-78%	-23%	-4%	-2%	-4%
Organ transplant other than kidney																				
No	100%	$ 2,493	$ 1,211	$ 1,282	$ 327	$ 954	$ 955	$ 626	$ 328	$ 1,288	$1,283	$1,282	$ 1,282	$1,282	0%	0%	0%	0%	0%
Yes	0%	$10,653	$ 2,959	$ 7,695	$5,403	$ 2,292	$2,020	$1,692	$ 328	$ 1,288	$6,358	$7,423	$ 7,598	$7,529	-498%	-21%	-4%	-1%	-2%
Kidney transplant status																				
No	100%	$ 2,471	$ 1,205	$ 1,266	$ 315	$ 951	$ 951	$ 623	$ 328	$ 1,288	$1,271	$1,266	$ 1,266	$1,266	2%	0%	0%	0%	0%
Yes	0%	$10,476	$ 3,245	$ 7,231	$4,917	$ 2,314	$2,248	$1,919	$ 328	$ 1,288	$5,873	$7,165	$ 7,172	$7,165	-462%	-23%	-1%	-1%	-1%
Breast/Prostate Cancer																				
No	92%	$ 2,494	$ 1,209	$ 1,285	$ 333	$ 952	$ 954	$ 626	$ 328	$ 1,288	$1,289	$1,287	$ 1,287	$1,287	0%	0%	0%	0%	0%
Yes	8%	$ 2,574	$ 1,254	$ 1,320	$ 316	$ 1,003	$ 973	$ 645	$ 328	$ 1,288	$1,272	$1,289	$ 1,294	$1,289	-2%	-4%	-2%	-2%	-2%
COPD																				
No	85%	$ 2,338	$ 1,138	$ 1,200	$ 286	$ 914	$ 928	$ 599	$ 328	$ 1,288	$1,242	$1,214	$ 1,214	$1,214	7%	3%	1%	1%	1%
Yes	15%	$ 3,451	$ 1,648	$ 1,803	$ 601	$ 1,202	$1,119	$ 791	$ 328	$ 1,288	$1,556	$1,720	$ 1,763	$1,734	-40%	-16%	-5%	-2%	-4%
Kidney failure																				
No	98%	$ 2,461	$ 1,197	$ 1,264	$ 318	$ 946	$ 948	$ 619	$ 328	$ 1,288	$1,274	$1,266	$ 1,266	$1,266	2%	1%	0%	0%	0%
Yes	2%	$ 4,058	$ 1,831	$ 2,227	$ 885	$ 1,342	$1,274	$ 946	$ 328	$ 1,288	$1,841	$2,160	$ 2,186	$2,161	-73%	-21%	-3%	-2%	-3%

CHF																				
No	86%	$ 2,319	$ 1,126	$ 1,193	$ 289	$ 904	$ 918	$ 590	$ 328	$ 1,288	$1,244	$ 1,207	$ 1,207	$1,207	7%	4%	1%	1%	1%
Yes	14%	$ 3,603	$ 1,742	$ 1,861	$ 594	$ 1,267	$1,183	$ 854	$ 328	$ 1,288	$1,549	$ 1,777	$ 1,819	$1,789	-45%	-20%	-5%	-2%	-4%
Hypertension																				
No	50%	$ 1,932	$ 918	$ 1,014	$ 275	$ 739	$ 809	$ 481	$ 328	$ 1,288	$1,230	$ 1,084	$ 1,045	$1,069	21%	18%	6%	3%	5%
Yes	50%	$ 3,059	$ 1,502	$ 1,557	$ 388	$ 1,168	$1,100	$ 771	$ 328	$ 1,288	$1,344	$ 1,488	$ 1,520	$1,495	-21%	-16%	-5%	-2%	-4%
Diabetes																				
No	79%	$ 2,224	$ 1,075	$ 1,149	$ 274	$ 875	$ 891	$ 563	$ 328	$ 1,288	$1,229	$ 1,165	$ 1,165	$1,165	11%	7%	1%	1%	1%
Yes	21%	$ 3,559	$ 1,740	$ 1,819	$ 555	$ 1,264	$1,203	$ 874	$ 328	$ 1,288	$1,510	$ 1,757	$ 1,781	$1,758	-41%	-20%	-3%	-2%	-3%
AIDS																				
No	100%	$ 2,483	$ 1,209	$ 1,274	$ 321	$ 953	$ 953	$ 625	$ 328	$ 1,288	$1,277	$ 1,275	$ 1,275	$1,275	1%	0%	0%	0%	0%
Yes	0%	$11,368	$ 3,165	$ 8,203	$5,861	$ 2,342	$2,125	$1,797	$ 328	$ 1,288	$6,816	$ 7,986	$ 8,114	$8,043	-537%	-20%	-3%	-1%	-2%

Source: Analysis of pooled MCBS Cost and Use files, 1997-2001.
Notes:
Average total drug spending was inflated across-the-board to an average of $2500, no adjustments for prices or induced demand, no plan overhead costs were added.
Population consists of persons in two successive MCBS samples, 1997 to 2001, excluding HMO enrollees, part or full year facility residents, persons in hospice, and MCBS "ghosts".
Risk adjustment is most current CMS model, calibrated on MCBS sample.
Under the "No Risk Protections" scenario, total plan revenue consists of premiums plus the all-dataset-average value of reinsurance dollars.

Implications for Further Research

The analyses conducted as part of this study support the conclusion that the ultimate model developed and put forward by CMS is quite reasonable and defensible from clinical, statistical, and policy perspectives. However, as indicated previously, the most serious problem with the model may be related to the lack of a common data set that would allow estimation of the model simultaneously for the full range of covered sub-populations. This applies most importantly to low-income persons and beneficiaries under 65 years of age, but also to institutionalized beneficiaries. Because of these limitations, underlying issues regarding refinement of the functional form, for example, received less attention than was perhaps ideal.

Thus, with regard to the risk adjustment model, there are several logical 'next steps.' Most obviously, these could include exploration of the availability of additional data sets for further assessment of the model as well as refinement of the underlying model specification. However, which of these steps to take or how to prioritize them depends heavily on the information that will be available to CMS from the plans themselves. Clearly, further refinement of the model would ideally be done on data recounting actual experience of Medicare beneficiaries enrolled in either MA plans or PDPs. This approach would provide the maximum information on beneficiary health status and prescription drug use with full knowledge of the benefit structure faced by the beneficiary. While the Secretary has clear authority to obtain data from the plans with which to study risk adjustment, it is not clear when these data will be available and ready for analysis and it is possible that these data may not be useable until 2007 or 2008. A sense of the timeline for obtaining data is critical in making informed decisions about further work on the model.

Assuming that the plan data are not available in the short run, there are several possible avenues for research to support the continued implementation of the drug benefit.

Using additional data sets to refine sub-population adjustments. One of the biggest concerns about the final model put forth by CMS was the low-income adjustment. In the end, the adjustments were derived outside the model largely using analyses of MCBS because MCBS was the only available data set with beneficiaries from a range of income levels as well as persons with and without drug coverage. Similarly, there were some reservations about the adjustment for institutionalized beneficiaries and the treatment of less-than-65 beneficiaries under the model. With additional time, it may be possible to explore other data sets that might support further analyses of these groups. In addition to the recent availability of the 2002 MCBS, it may be possible to obtain private health plan data with a broader range of benefit structures and beneficiary incomes than offered by the FEP data.

Refinement of model specification. As mentioned earlier, the lack of high quality data to some extent hampered the level of attention paid to model specification. Thus, there may be additional ways to improve the predictive power of the model by reexamining whether particular measures should be included and, if so, how they should be included. For example, it is likely to be important to adjust payments for low-income beneficiaries, because of both expected effects on utilization of being low-income and the special subsidies that

will be paid for these beneficiaries. Although it is clear that low-income status should be included in the model, it is not clear whether it should be included as a simple dummy variable, resulting in a fixed payment difference due to being low income, or as a dummy variable interacted with the scores of diagnostic indicators, resulting in payments for these beneficiaries that reflect both their low-income status as well as their particular diseases. Apart from the low-income adjustment, other aspects of how various variables are entered into the model may be worth exploring, for example, whether co-morbidities act in a more-than-linear fashion, so that some of the variation is in fact interactions of co-morbidities that are not picked up by the (linear) risk model.

In-depth analysis of geographic variation in utilization. The risk adjustment model accounts for regional variation in utilization related to variations in prevalence of disease. Remaining regional (risk-adjusted) variation in spending may be due to variations in intensity of drug therapy within disease classes, largely reflecting presumed variations in the practice of medicine but also potentially influenced by such factors as individual wealth and education, as well as to differences in health status not captured by the current set of risk adjusters. Further research should explore the nature of variation more fully, for example, looking at rates of utilization without the potentially confounding effect of price. Some evidence that patterns differ across therapeutic categories suggests the importance of looking at use in major categories.

In addition, to ensure that the plan bids and beneficiary premiums are equitable and providing appropriate incentives, it is useful to better understand what accounts for the variation in volume and intensity of drug utilization across geographic areas. Preliminary evidence that the presence of more drug stores and fewer HMOs is associated with higher spending suggests that system-level factors may be important. A few of the potential issues that might be explored would include: what diseases contribute most to the variation; and how the variation is influenced by the number of drugs used for a given diagnosis, the dosage, or the use of generics vs. newer drugs; and whether there are interactions among diagnoses.

Examination of drug spending inflation. Another key question related to the financing of the benefit is the likely rate of inflation of spending. With several years of data, it may be possible to examine, for example, person-level three-year profiles of spending trends over time. Many of the questions would be similar in nature to the analysis of variation in regional drug spending described above. After accounting for time trends in diagnoses, what causes drug spending to rise faster for certain individuals than for others?

Finally, in terms of operation of the system, the central research question is whether competition is adequate to force relatively efficient behavior by the drug plans and whether these plans collectively provide pricing pressure on the drug manufacturers. One aspect of this is formulary-based competition which is being addressed in part by another ASPE-funded project. Assessing interactions between the formulary drug classification schemes and the risk adjustment model may also warrant some consideration.

Appendix. Additional Tables

Figure A-1. Retail Pharmacies Included in Retail Price Analysis

State	Total Retail Pharmacies in State	Retail Pharmacies in Sample	% of Retail Pharmacies Included
Alabama	1,142	552	48%
Alaska	77	42	54%
Arizona	832	411	49%
Arkansas	693	202	29%
California	4,753	2,768	58%
Colorado	677	363	54%
Connecticut	585	240	41%
Delaware	157	82	52%
District of Columbia	92	42	46%
Florida	3,348	1,163	35%
Georgia	1,816	777	43%
Hawaii	147	46	31%
Idaho	244	106	43%
Illinois	2,101	695	33%
Indiana	1,052	486	46%
Iowa	695	308	44%
Kansas	537	182	34%
Kentucky	948	404	43%
Louisiana	1,036	398	38%
Maine	244	146	60%
Maryland	944	444	47%
Massachusetts	981	450	46%
Michigan	1,997	977	49%
Minnesota	870	335	38%
Mississippi	730	254	35%
Missouri	1,018	301	30%
Montana	200	91	46%
Nebraska	392	134	34%
Nevada	384	248	64%
New Hampshire	219	128	58%
New Jersey	1,762	706	40%
New Mexico	232	76	33%
New York	3,928	1,752	45%
North Carolina	1,575	724	46%
North Dakota	159	111	70%
Ohio	2,090	1,183	57%
Oklahoma	747	205	27%
Oregon	582	353	61%
Pennsylvania	2,597	1,204	46%
Puerto Rico	873	225	26%
Rhode Island	177	97	55%
South Carolina	879	366	42%
South Dakota	165	83	50%
Tennessee	1,273	452	36%
Texas	3,550	1,259	35%
Utah	374	193	51%
Vermont	124	79	64%
Virginia	1,278	560	44%
Washington	1,036	527	51%
West Virginia	443	254	57%
Wisconsin	881	216	25%
Wyoming	107	46	43%
TOTAL	53,743	23,444	44%

Figure A-2. Drugs Included in Analysis of Geographic Variation in Prices

Leading Therapeutic Classes (TC) / Leading Products within Class	Manufacturer	% of TC Rxs	Cumulative % of TC Rxs
ANTIDEPRESSANTS			
ZOLOFT	Pfizer	17.4%	17.4%
LEXAPRO	Forest	14.2%	31.6%
CELEXA	Forest	6.4%	38.0%
EFFEXOR XR	Wyeth-Ayerst	5.8%	43.8%
ANTIPSYCHOTICS			
RISPERDAL	Janssen	26.5%	26.5%
ZYPREXA	Lilly	25.1%	51.6%
SEROQUEL	AstraZeneca	21.0%	72.6%
ABILIFY	Otsuka America Ph	3.8%	76.4%
ANTI-ULCERANTS			
PROTONIX	Wyeth-Ayerst	28.5%	28.5%
RANITIDINE	Generic	19.0%	47.5%
PREVACID	TAP	18.5%	66.0%
NEXIUM	AstraZeneca	4.5%	70.5%
ACIPHEX	Eisai	2.2%	72.7%
SEIZURE DISORDERS			
NEURONTIN	Pfizer	21.1%	21.1%
DEPAKOTE	Abbott	13.2%	34.3%
CLONAZEPAM	Generic	11.3%	45.6%
DILANTIN	Pfizer	6.3%	51.9%
DEPAKOTE ER	Abbott	5.2%	57.1%
ADRENERGIC BLOCKER			
METOPROLOL TART	Generic	26.2%	26.2%
TOPROL-XL	AstraZeneca	15.7%	41.9%
COREG	GSK	6.5%	48.4%
CATAPRES TTS	B.I.	3.8%	52.2%
RENIN ANGIOTENSIN ANTAGONISTS			
LISINOPRIL	Generic	35.0%	35.0%
DIOVAN	Novartis	7.7%	42.7%
ALTACE	Monarch Pharm	6.7%	49.4%
COZAAR	Merck	5.8%	55.2%
ANTI-INFECTIVES, BROAD & MEDIUM SPECTRUM			
LEVAQUIN	McNeil	20.4%	20.4%
CEPHALEXIN	Generic	11.8%	32.2%
ZITHROMAX	Pfizer	6.4%	38.6%
CIPRO	Bayer	5.7%	44.3%
ANTIANXIETY			
LORAZEPAM	Generic	46.7%	46.7%
ALPRAZOLAM	Generic	20.3%	67.0%

BUSPIRONE HCL	Generic	9.7%	76.7%
Leading Therapeutic Classes (TC) / Leading Products within Class	**Manufacturer**	**% of TC Rxs**	**Cumulative % of TC Rxs**
ANTI-COAGULANTS			
WARFARIN SODIUM	Generic	45.0%	45.0%
COUMADIN	Dupont Pharm	36.0%	81.0%
LOVENOX	Aventis	9.4%	90.4%
THYROID HORMONE			
SYNTHROID	Abbott	40.9%	40.9%
LEVOXYL	Jones Pharmaceutic	25.8%	66.7%
LEVOTHROID	Forest	15.8%	82.5%
CHOLESTEROL REDUCERS			
LIPITOR	Pfizer	49.3%	49.3%
ZOCOR	Merck	19.8%	69.1%
PRAVACHOL	Bristol-Myers Squibb	7.8%	76.9%
ZETIA	Merck/Schering Plough	3.1%	80.0%
BRONCHODILATORS GENERAL			
ALBUTEROL	Generic	40.9%	40.9%
DUONEB	Dey Labs	11.7%	52.6%
COMBIVENT	B.I.	10.0%	62.6%
XOPENEX	Sepracor	5.3%	67.9%
ATROVENT	B.I.	3.1%	71.0%
DIABETES, ORAL			
METFORMIN HCL	Generic	21.7%	21.7%
AVANDIA	GSK	10.3%	32.0%
ACTOS	Takeda	10.0%	42.0%
AMARYL	Aventis	7.8%	49.8%
ANTI-ARTHRITICS, SYSTEMIC			
CELEBREX	Pfizer	36.8%	36.8%
VIOXX	Merck	20.7%	57.5%
BEXTRA	Pfizer	9.4%	66.9%
ALZHEIMER-TYPE DEMENTIA			
ARICEPT	Eisai	60.3%	60.3%
REMINYL	Janssen	14.8%	75.1%
EXELON	Novartis	13.7%	88.8%
NAMENDA	Forest	11.2%	100.0%
BONE DENSITY REGULATORS			
ACTONEL	P&G	33.4%	33.4%
FOSAMAX	Merck	31.9%	65.3%
MIACALCIN	Novartis	23.1%	88.4%
EVISTA	Lilly	10.9%	99.3%

Figure A-3. Number of Prescriptions Included in Retail Price Analysis

State	All Prescriptions for Pharmacies in Sample	Prescriptions for Drugs in Market Basket		
		Total Prescriptions	With third party payment	No third party payment
Alabama	2,603,671	1,119,222	861,781	118,932
Alaska	238,882	109,947	72,884	10,653
Arizona	1,697,873	805,711	686,174	33,905
Arkansas	768,250	321,250	211,708	49,558
California	13,825,139	6,125,079	4,293,225	332,227
Colorado	1,529,206	715,550	545,035	57,077
Connecticut	1,658,917	849,575	651,896	57,924
Delaware	480,984	243,310	197,636	14,494
District of Columbia	199,295	116,942	77,961	10,651
Florida	3,548,711	1,657,410	1,212,945	135,024
Georgia	3,706,980	1,624,568	1,173,272	176,850
Hawaii	460,934	236,537	189,671	11,718
Idaho	435,473	213,666	153,170	18,927
Illinois	3,485,448	1,807,792	1,393,983	97,078
Indiana	2,977,888	1,413,950	1,061,754	123,567
Iowa	1,273,360	619,854	479,630	56,813
Kansas	980,504	466,037	337,592	43,601
Kentucky	2,191,238	1,007,289	716,571	99,355
Louisiana	1,260,491	526,321	373,432	54,403
Maine	781,548	430,910	243,400	19,644
Maryland	2,035,872	937,879	716,432	60,631
Massachusetts	3,366,146	1,845,446	1,338,506	95,843
Michigan	4,848,788	2,316,530	1,885,041	111,878
Minnesota	1,530,899	805,686	619,290	57,173
Mississippi	946,732	382,545	241,909	47,923
Missouri	1,471,619	661,980	450,713	44,605
Montana	348,310	165,315	110,936	25,105
Nebraska	475,467	227,464	175,548	24,581
Nevada	997,205	445,379	349,225	26,632
New Hampshire	824,062	409,329	303,310	29,241
New Jersey	3,473,472	1,644,957	1,280,501	91,843
New Mexico	266,752	123,023	93,491	9,855
New York	9,075,574	4,458,140	3,025,146	199,032
North Carolina	4,248,877	1,987,309	1,307,698	196,591
North Dakota	376,931	177,516	106,663	33,982
Ohio	6,606,923	3,193,270	2,217,369	226,310
Oklahoma	777,210	330,614	244,291	35,815
Oregon	1,691,941	728,424	538,000	68,033
Pennsylvania	6,606,514	3,290,037	2,763,284	152,466
Puerto Rico	699,749	200,822	148,533	37,470
Rhode Island	910,023	449,873	361,634	15,940
South Carolina	2,048,031	899,085	632,418	80,001
South Dakota	309,430	141,685	97,147	19,671
Tennessee	2,839,886	1,335,709	866,648	112,503
Texas	5,065,242	2,148,924	1,569,099	246,484
Utah	942,711	451,683	339,183	32,162
Vermont	401,594	206,754	116,253	10,265
Virginia	2,842,757	1,299,092	1,003,019	105,827
Washington	2,325,430	1,058,425	727,413	99,480
West Virginia	1,348,509	646,444	454,570	46,949
Wisconsin	963,150	458,858	327,504	26,516
Wyoming	157,192	76,316	51,810	11,579
TOTAL	114,927,791	53,915,433	39,396,304	3,904,787

Figure A-4. Explanatory Variables Tested and sources

Factor	Source
Population density (number per square mile)	U.S. Census Bureau, Census 2000 Summary File 1
Percent of the population living in a metropolitan area	U.S. Census Bureau, Census 2000 Summary File 1
Percent with a Bachelor's degree or higher	U.S. Census Bureau, 2003 Current Population Survey
Median Income	U.S. Census Bureau, Current Population Survey, 2002, 2003, and 2004 Annual Social and Economic Supplements
Medicare beneficiaries as a percent of population	Kaiser Family Foundation (KFF) State Health Facts. Based on data from CMS and Census.
Medicaid beneficiaries as a percent of population	KFF State Health Facts. Based on data from CMS and Census.
Percent of the population 19-64 with employer coverage	KFF State Health Facts. based on pooled March 2002 and 2003 Current Population Surveys.
Percent of the population 19-64 uninsured	KFF State Health Facts. based on pooled March 2002 and 2003 Current Population Surveys.
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
Percent of the population at risk for heavy drinking	BRFSS, 2003
Percent of the population at risk for high cholesterol	BRFSS, 2003
Percent of the population with diabetes (not pregnancy related)	BRFSS, 2003
Percent of the population at risk for asthma	BRFSS, 2003
Percent with Hypertension	BRFSS, 2003
Percent at risk for smoking related illness	BRFSS, 2003
Physicians per 100,000 population	KFF State Health Facts. Taken from American Medical Association, Physicians Professional Data, and Census.
Pharmacies per 1,000 population	NORC Computation using NACDS and Census data
Chain drug stores as a percent of all pharmacies	National Association of Chain Drug Stores (NACDS) Chain Pharmacy Industry Profile 2003
Mass merchant pharmacies as a percent of all pharmacies	National Association of Chain Drug Stores (NACDS) Chain Pharmacy Industry Profile 2003
Supermarket pharmacies as a percent of all pharmacies	NACDS Chain Pharmacy Industry Profile 2003
Independent pharmacies as a percent of all pharmacies	NACDS Chain Pharmacy Industry Profile 2003
Median annual pharmacists wages	Bureau of Labor Statistics, 2003
Median monthly apartment rent	2000 Census: Summary File 3 (SF 3), Table GCT-H9: Financial Housing Characteristics.

Figure A-5. HHS Regions

Region 1 (Boston)
Connecticut
Maine
Massachusetts
New Hampshire
Rhode Island
Vermont

Region 2 (New York)
New Jersey
New York

Region 3 (Philadelphia)
Delaware
District of Columbia
Maryland
Pennsylvania
Virginia
West Virginia

Region 4 (Atlanta)
Alabama
Florida
Georgia
Kentucky
Mississippi
North Carolina
South Carolina
Tennessee

Region 5 (Chicago)
Illinois
Indiana
Michigan
Minnesota
Ohio
Wisconsin

Region 6 (Dallas)
Arkansas
Louisiana
New Mexico
Oklahoma
Texas

Region 7 (Kansas City)
Iowa
Kansas
Missouri
Nebraska

Region 8 (Denver)
Colorado
Montana
North Dakota
South Dakota
Utah
Wyoming

Region 9 (San Fransisco)
Arizona
California
Hawaii
Nevada

Region 10 (Seattle)
Alaska
Idaho
Oregon
Washington

Source: US Department of Health and Human Services.