

Risk Adjustment for Medicare Beneficiaries With Alzheimer's Disease and Related Dementias

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Until Medicare added diagnoses to risk adjustment methods (ie, including factors such as age, sex, county, institutional status, and Medicaid eligibility) to pay Medicare Advantage (MA) plans in 2000, policy makers and researchers were concerned that Medicare was overpaying these plans due to favorable selection of beneficiaries.¹ The current Medicare capitation model, the Centers for Medicare & Medicaid version of the Diagnostic Cost Group–Hierarchical Condition Category (CMS-HCC),² appears to address these historic concerns for the average beneficiary. However, risk-adjusted payment methods merit re-examination because the increasing prevalence of high-cost diseases coupled with increasing disability and frailty may worsen underprediction (and underpayment) for high-cost beneficiaries. For instance, the CMS-HCC may not adequately compensate health plans serving primarily disabled or frail populations.³⁻⁵ Underpayment creates disincentives for managed care plans to enroll beneficiaries with greater healthcare needs,⁵ which will not achieve the efficiency goals of the MA program.⁶

Many comparisons of risk adjustment and comorbidity measures are available for general populations, but there is much less examination of whether measures that perform best in general populations also perform best in disease-specific populations.⁷⁻¹⁰ In this analysis, we contrasted the CMS-HCC measure with others in predicting total health expenditures and drug expenditures among Medicare beneficiaries with Alzheimer's disease and related dementias (ADRD) who have prominent functional disabilities. The CMS-HCC measure does not account for ADRD, thus providing a venue for testing its accuracy in comparison with other measures that account for dementia.

Survey-reported functional status, which is particularly important for chronically ill and frail populations, may complement claim-based diagnosis information to improve expenditure prediction for payment setting because functional status is not considered in claims-based measures.⁵ Therefore, we examined whether the addition of this frailty adjustment improved performance compared with single-measure models. We also examined the performance of these measures with respect

to their broader use as a managerial tool for identifying a subgroup of frail, high-cost beneficiaries, which could inform efforts to target patients who may be amenable to medical management and cost-containment interventions.^{11,12}

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Objective: To compare prospective risk adjustment measures on their ability to predict expenditures for Medicare beneficiaries with Alzheimer's disease and related dementias (ADRD).

Methods: Data were obtained from the 1999-2004 Medicare Current Beneficiary Survey linked with Medicare claims. Beneficiaries' base-year demographic and health characteristics were used to construct risk adjustment measures, comorbidity measures, functional status measures, and prior expenditures that were used to predict the subsequent year's total and drug expenditures. Adjusted R^2 values, predictive ratios, and receiver operating characteristic curves were used to compare overall predictive power, accuracy of subgroup prediction, and accuracy in identifying beneficiaries with the top 10% of expenditures, respectively.

Results: The Centers for Medicare & Medicaid Services–Hierarchical Condition Category (CMS-HCC) and the Chronic Illness and Disability Payment System–Medicare had higher overall and subgroup predictive power for total expenditures compared with other diagnosis-based measures. The Prescription Drug Hierarchical Condition Category (RxHCC) exhibited greater predictive power for drug expenditures than other measures and outperformed other measures in identifying ADRD beneficiaries with extremely high drug expenditures. Adding functional status to single-measure models generally improved predictive power (ie, R^2 value) for overall health expenditures by 2% to 4%, but not for drug expenditures.

Conclusions: The CMS-HCC and the RxHCC measures currently used by CMS are more predictive and accurate than other risk adjustment measures for overall and drug expenditure prediction for beneficiaries with substantial disabilities and comorbidities. Prediction of overall expenditures may be modestly improved for these beneficiaries by using a combined model of these measures and functional status.

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For author information and disclosures, see end of text.

Take-Away Points

Overall expenditure prediction may be modestly improved for beneficiaries with substantial disabilities and comorbidities, such as those with Alzheimer's disease and related dementias, by incorporating functional status.

- Prior expenditures outperformed all other measures in the overall sample, the lower-cost group, and the higher-cost group, and can be used as a screening tool for high-cost case identification.
- The Prescription Drug Hierarchical Condition Category measure currently used by Medicare is more predictive and accurate than other diagnosis-based risk adjustment measures for predicting prescription costs.

Measures

Dependent Variables: Total Health Expenditures and Prescription Drug Expenditures. Six dependent variables were examined: (1) total health-care expenditures, (2) prescription drug expenditures, (3) quartiles of total expenditures, (4) quartiles of drug expenditures, (5) top 10% of total expenditures, and (6) top 10% of drug ex-

pensitures. Total healthcare expenditures were defined in the MCBS as the sum of expenditures by Medicare, Medicaid, private insurance, out-of-pocket payments, and other sources across all types of services. Drug expenditures, a critical issue in managing ADRD,²¹ were defined as MCBS-imputed total payments for any prescription drugs paid by all sources.²²

To assess whether higher- and lower-cost beneficiaries were under- or overpredicted, total and drug expenditures in year $t + 1$ were arranged in descending order and categorized into quartiles. We used a top-10% expenditure threshold and evaluated the measures' ability to identify these high-cost beneficiaries. All expenditures were converted into constant 2007 dollars and were annualized by dividing them by the fraction of available person-days in a given year; all analyses were weighted by this fraction.^{19,20}

Explanatory Variables: Risk Adjustment, Comorbidity, and Frailty Adjustment Measures

CENTERS FOR MEDICARE & MEDICAID SERVICES HIERARCHICAL CONDITION CATEGORY. We used the 2007 CMS-HCC measure, which was recalibrated using more recent data (ie, 2002-2003).²³ Hierarchies are imposed among related Condition Categories ($n = 189$) to form 70 Hierarchical Condition Categories, to which "offered weights" (ie, payment weights provided by the software)²⁴ are assigned. We calculated the CMS-HCC score for each beneficiary by summing the weights in the standard community model.

CHRONIC ILLNESS AND DISABILITY PAYMENT SYSTEM—MEDICARE. We used the Chronic Illness and Disability Payment System²⁵ Medicare version (CDPSM) with 16 major disease categories, which are divided further into 66 subcategories.²⁶ Offered weights are assigned among subcategories to reflect the level of increased expenditures. The CDPSM score is the sum of the weights for all indicated subcategories, including a higher-cost subcategory of delirium and a lower-cost subcategory of dementia (see [eAppendix](#) available at www.ajmc.com for the complete list of ADRD-related ICD-9-CM diagnosis codes).

PRESCRIPTION DRUG HIERARCHICAL CONDITION CATEGORY. The Prescription Drug Hierarchical Condition Category

METHODS

Data Source and Sample

We analyzed data from the 1999-2004 Medicare Current Beneficiary Survey (MCBS) Cost and Use files, linked with Medicare Part A and Part B claims data.¹³ Information on prescription drug use was recorded from the survey. Elderly, community-dwelling beneficiaries (including those eligible for both Medicare and Medicaid), defined as adults age 65 years and older who were not institutionalized for more than 90 consecutive days during a year, were selected ($N = 57,669$). From these individuals, 2447 beneficiaries with 3606 person-year observations were identified as having ADRD, based on any of the following criteria^{14,15}: (1) self or proxy report of ADRD; (2) the presence of any of the following diagnosis codes indicating ADRD in Medicare claims files^{16,17}: all 290 codes, 291.2, 292.82, 294.1, 294.8, 331.0-331.2, and 797 defined by the *International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM)* diagnosis codes; or (3) use of any ADRD-targeted medications (ie, donepezil [Aricept], rivastigmine [Exelon], galantamine [Reminyl or Razadyne], memantine [Namenda]).

We then excluded 266 MA enrollees representing 438 person-year observations, because managed care plans were not required to submit claims with diagnoses to CMS in 1999-2004, to generate a sample of 2181 beneficiaries representing 3168 person-year observations. With the application of MCBS sampling weights, our sample was representative of 1.21 million to 1.91 million ADRD beneficiaries annually during 1999-2004, which is consistent with estimates from epidemiologic studies.¹⁸ We retained beneficiaries with less than full-payment year (ie, year $t + 1$) information to capture the potentially different expenditure pattern of decedents and nonrespondents.^{19,20} As a result, a 2-year panel of 1452 person-year observations representing 726 unique beneficiaries was analyzed, after excluding death or survey nonresponse during the base year t ($n = 1455$) and data for year $t + 2$ among beneficiaries who were observed in 3 years of MCBS data ($n = 261$).

(RxHCC) is a diagnosis-based model that CMS currently uses to adjust payments to Medicare prescription drug plans.¹⁹ Hierarchies are imposed among 197 Rx Condition Categories to create 89 RxHCCs. There are 2 ADRD-related RxHCCs: dementia with depression or behavioral disturbance, and dementia/cerebral degeneration (**eAppendix**). The RxHCC score is the sum of the offered weights for all indicated conditions.

CHARLSON COMORBIDITY INDEX. We used the Charlson Comorbidity Index (CCI) with the Deyo modification, which has 17 comorbidity categories including dementia (**eAppendix**).^{27,28} Each condition is assigned a weight of 1, 2, 3, or 6, reflecting the magnitude of the adjusted relative risks associated with each comorbidity. The CCI score is calculated as the sum of the offered weights for all indicated conditions.

FRAILTY ADJUSTMENT. Limitations in activity of daily living (ADL), a critical part of the ADRD progression, may exacerbate other chronic conditions; thus, ADRD beneficiaries incur persistently high expenditures over time.^{29,30} The frailty adjuster used here was the count of difficulty in performing ADLs, categorized as none, 1-2 (low), 3-4 (moderate), or 5-6 (high), as defined in the CMS frailty adjustment model.³

PRIOR EXPENDITURES. Prior expenditures are highly correlated with expenditures in the following year.^{12,31} We used total healthcare expenditures in year t for total expenditure models, and drug expenditures in year t for drug expenditure models.

COMBINED MODELS. Beginning in 2004, ADL limitations were used concurrently with the CMS-HCC measure to adjust the payments made to selected organizations (eg, Program of All-Inclusive Care for the Elderly).³ We compared the performances of single-measure models and combined models by including ADL limitations into diagnosis-based models and prior-expenditure models. All models controlled for age (categorized as 65-69, 70-74, 75-79, 80-84, and 85+ years) and sex.

Analysis

Expenditures in prediction year $t + 1$ were regressed on each risk adjustment measure plus sex and age categories at year t using ordinary least squares (OLS) regression. We also performed a sensitivity analysis using a generalized linear model (GLM) to assess whether alternative distributions changed the relative ranking of measures' predictive power,⁹ and used a modified Park test to determine the type of GLM to be used.³² We used adjusted R^2 values from the OLS models and log likelihood values from the GLMs to assess overall prediction, with higher numbers indicating better model fit to estimate mean expenditures.

We computed predictive ratios (ie, predicted expenditures divided by actual expenditures) by quartile to assess the degree of overprediction or underprediction of expenditures in subgroups.^{31,33} Measures with less overprediction in upper quartiles and less underprediction in lower quartiles (indicated by predictive ratios closer to 1.0) are preferred. Then, we used receiver operating characteristic curves to identify the highest-spending 10% of the sample.¹¹ A C statistic representing the area under the receiver operating characteristic curve was calculated. A value of 0.5 indicates no ability to discriminate; higher values between 0.5 and 1.0 indicate a better model fit.

RESULTS

Descriptive Statistics

The average age of our sample was 81.3 years and 60% were female (**Table 1**). The mean CMS-HCC, CDPSM, RxHCC, and CCI scores all were greater than 1.0, indicating a higher comorbidity burden than that observed in the general Medicare population. On average, beneficiaries with ADRD had 1.3 ADL limitations. Average total expenditures were \$24,952 (in 2007 constant dollars) and average prescription drug expenditures were \$2659 in year $t + 1$.

Overall Prediction

All diagnosis-based measures explained more variation in total expenditures than in drug expenditures (**Table 2**). In predicting total expenditures, the CMS-HCC and the CDPSM had higher adjusted R^2 values (14.7% and 14.9%, respectively) compared with the CCI (8.4%), the RxHCC (6.0%), and ADLs alone (2.8%). Incorporating ADLs modestly increased the adjusted R^2 of the diagnosis-based models, with the CMS-HCC and CDPSM remaining the most predictive (15.1% and 15.4%, respectively). Prior expenditures alone were more predictive (adjusted $R^2 = 20.4%$) than diagnoses plus ADLs.

In predicting drug expenditures, the RxHCC model explained nearly 10% of the variation, whereas other diagnosis-based models had less explanatory power (adjusted $R^2 = 1.8\%$ - 2.7%). Prior drug expenditures had the greatest explanatory power (adjusted $R^2 = 38.7\%$). Surprisingly, incorporating ADL limitations decreased the adjusted R^2 in all cases, indicating that ADLs failed to add statistical improvement to the models. Sensitivity analysis suggested a similar ranking of measures with GLM regressions.

Predictive Accuracy by Expenditure Quartile

Based on predictive ratios, all models substantially underpredicted total expenditures in the highest quartile and overpredicted those expenditures in the lowest quartile (**Table 3**).

Table 1. Descriptive Statistics of Sample Beneficiaries With Alzheimer’s Disease and Related Dementias

Characteristic	Percent or Mean (SD)	Minimum	Maximum
Age, y	81.30 (7.08)	65	101
65-69	6.75	—	—
70-74	12.95	—	—
75-79	17.49	—	—
80-84	29.89	—	—
85+	32.92	—	—
Male	39.67	—	—
CMS-HCC	1.73 (1.33)	0.30	8.82
CDPSM	1.73 (1.22)	0.17	7.49
CCI	1.61 (1.54)	0	16.00
RxHCC	1.18 (0.45)	0.30	2.84
Count of ADL limitations	1.32 (1.97)	—	—
0	60.33	—	—
1-2	15.70	—	—
3-4	10.88	—	—
5-6	13.09	—	—
Total expenditures, 2007 \$			
Year <i>t</i>	17,776 (22,230)	0	219,992
Year <i>t</i> + 1	24,952 (49,548)	0	623,954
Drug expenditures, 2007 \$			
Year <i>t</i>	2347 (2224)	0	24,832
Year <i>t</i> + 1	2659 (2749)	0	36,415

ADL indicates activity of daily living; CCI, Charlson Comorbidity Index; CDPSM, Chronic Illness and Disability Payment System–Medicare; CMS-HCC, Centers for Medicare & Medicaid Services version of the Diagnostic Cost Group–Hierarchical Condition Category; RxHCC, Prescription Drug Hierarchical Condition Category.

Predictive accuracy was better for the prior expenditure models. The CMS-HCC and CDPSM measures exhibited less underprediction in the highest quartile and less overprediction in the lowest quartile relative to other diagnosis-based measures, suggesting that CMS-HCC and CDPSM performed better in the low-cost group, the high-cost group, and in the overall sample. Adding ADLs modestly improved the predictive accuracy in each expenditure quartile.

In predicting drug expenditures, all models performed well for the middle 50% of beneficiaries, but underpredicted drug expenditures in the highest quartile by approximately 50%, and overpredicted those in the lowest quartile by nearly 7-fold (Table 4). Prior drug expenditures outperformed the RxHCC, which, in turn, outperformed other diagnoses in subgroups. Inclusion of ADLs did not improve prediction across drug expenditure quartiles.

Sensitivity analysis suggested that the GLM approach modestly improved predictive accuracy in the highest quartile

of total expenditures but overpredicted more in the lowest quartile compared with OLS models (results not shown). Prior drug expenditures with GLM regressions were generally consistent with the OLS results in Table 4.

Prediction of High Expenditures

The ability of the tested models to identify high-cost “outliers” is summarized in Table 5. Adding diagnoses to age and sex adjustment increased the C statistics, with the RxHCC being the most predictive of total expenditure models (C = 0.73). Adding ADL limitations modestly improved discrimination power. Prior expenditures alone were more predictive (C = 0.76) than diagnosis-based measures either with or without ADLs. Similar to the patterns observed for total expenditures, the RxHCC exhibited higher discrimination power than other diagnosis-based measures in identifying beneficiaries with the highest drug expenditures. Adding ADLs increased the C statistic of the RxHCC from 0.69 to 0.79, but did not result in an increase for other diagnosis-based measures. Prior drug expenditures had good discrimination power (C = 0.89) and outperformed all other measures.

DISCUSSION

Appropriate risk adjustment is essential to balance the healthcare needs of beneficiaries with greater disease burden, the financial viability of participating plans, and the stability of the MA program overall.² This delicate balance requires accurate prediction of mean expenditures and the expenditures of beneficiaries with above-average risk.⁵ We explored whether existing risk adjustment measures that perform best in general populations also perform best in a frail, high-cost ADRD population. Consistent with earlier research,^{31,34} we found that prior expenditures outperformed all other measures in the overall sample, explaining more than 20% of the variation in total expenditures and nearly 40% of the variation in drug expenditures. The results are likely due to the persistence of total and drug expenditures in the upper and lower percentiles, and to drug expenditures being more stable over time.^{12,35,36} Using prior expenditures to set prospective payment rates creates per-

Performance of Risk Adjustment Measures

Table 2. Adjusted R^2 Values and Predicted Means of Risk Adjustment Measures in Prospective Expenditure Models

Risk Adjustment Measures ^a	Adjusted $R^2 \times 100\%$ ^b		Log Likelihood Value ^c	
	Total Expenditures	Prescription Drug Expenditures	Total Expenditures	Prescription Drug Expenditures
Age and sex	0.01	0.40	-7956	-6208
Diagnosis-based measures				
CMS-HCC	14.67	1.81	-7862	-6203
CDPSM	14.90	2.36	-7861	-6201
CCI	8.43	2.73	-7895	-6199
RxHCC	6.02	9.87	-7899	-6173
Count of ADL limitations^d	2.81	0.54	-7929	-6206
Prior expenditures^e	20.40	38.73	-7851	-6047
Combined models				
CMS-HCC + count of ADL limitations	15.07	1.59	-7850	-6202
CDPSM + count of ADL limitations	15.43	2.13	-7847	-6200
CCI + count of ADL limitations	10.33	2.68	-7872	-6198
RxHCC + count of ADL limitations	8.10	9.72	-7874	-6172
Prior expenditures ^e + count of ADL limitations	20.45	38.52	-7843	-6046

ADL indicates activity of daily living; CCI, Charlson Comorbidity Index; CDPSM, Chronic Illness and Disability Payment System–Medicare; CMS-HCC, Centers for Medicare & Medicaid Services version of the Diagnostic Cost Group–Hierarchical Condition Category; RxHCC, Prescription Drug Hierarchical Condition Category.

^aAll models included the risk adjustment score as an independent variable along with demographic dummy variables for age (categorized as 65-69, 70-74, 75-79, 80-84, and 85+ years) and sex.

^bAdjusted R^2 values were obtained from weighted ordinary least squares regression.

^cLog likelihood values were obtained from a generalized linear model with gamma distribution and log link.

^dCount of ADL limitations was categorized as none, 1-2, 3-4, or 5-6.

^ePrior total expenditures were used in total expenditure models; prior drug expenditures were used in drug expenditure models.

verse incentives for overuse and for avoidance of beneficiaries with high-cost risk, but prior expenditures appear to be a powerful screening tool for identification of high-cost cases.^{11,12,37}

Although diagnosis-based measures may not be as predictive, they could be more useful for accurately reimbursing MA plans and prescription drug plans that enroll beneficiaries with particular comorbidities. We found that the predictive power of CMS-HCC (which does not account for ADRD) was comparable to that of CDPSM (which takes into account delirium and dementia). These 2 measures outperformed other diagnosis-based measures in subgroup prediction based on quartiles. In predicting drug expenditures, the RxHCC exhibited higher predictive power and predictive accuracy both overall and for subgroups than any other diagnosis-based measures. Although the RxHCC explained only 10% of the variation in drug expenditures, this diagnostic classification system appears to be an appropriate starting point for risk-adjusting prescription drug expenditures. It should be noted that beneficiaries' demographic and enrollment characteristics (such as age–sex interaction, reason for Medicare entitlement, and Medicaid eligibility) also may affect the model performance. These factors are incorporated into some mea-

asures (eg, CMS-HCC, CDPSM, RxHCC) but not others (eg, CCI). Further refinement, such as the inclusion of condition-specific baseline severity and clinical measures, is needed to improve predictive accuracy if such measures become available on a systematic population basis in Medicare claims.

Beginning in 2010, disabling chronic condition Special Needs Plans (SNPs), a type of specialized MA plan, may offer a plan benefit package that covers only 1 of the 15 SNP-specific conditions (eg, dementia). Because SNPs receive CMS-HCC–adjusted payments, as do other MA plans, but bear the full financial risk for the care of enrollees with substantial and complex healthcare needs, the issue of matching payments to medical complexity and cost becomes of paramount importance. Consistent with the findings in the general Medicare population,^{3,5} our data show that adding ADL limitations modestly improve the performance of risk adjustment models in predicting overall health expenditures. The results are possibly because functional disabilities are an important driver of elevated costs in ADRD.^{18,38} In high-cost outlier analysis, models combining ADLs and diagnoses had higher discrimination power ($C = 0.70$ - 0.77) than diagnoses alone. This discrimination power was higher than that ob-

■ **Table 3.** Predictive Ratios of Risk Adjustment Measures in Predicting Total Healthcare Expenditures

Risk Adjustment Measures ^a	Lowest Quartile	Second Lowest Quartile	Second Highest Quartile	Highest Quartile
Age and sex	7.43	2.82	1.23	0.28
Diagnosis-based measures				
CMS-HCC	5.42	2.53	1.30	0.41
CDPSM	5.17	2.53	1.33	0.41
CCI	5.97	2.67	1.30	0.35
RxHCC	5.74	2.69	1.34	0.34
Count of ADL limitations^b	6.89	2.74	1.28	0.32
Prior expenditures^c	4.81	2.38	1.34	0.44
Combined models				
CMS-HCC + count of ADL limitations	5.28	2.51	1.32	0.42
CDPSM + count of ADL limitations	5.01	2.50	1.35	0.42
CCI + count of ADL limitations	5.58	2.61	1.35	0.38
RxHCC + count of ADL limitations	5.36	2.63	1.38	0.37
Prior expenditures ^c + count of ADL limitations	4.72	2.37	1.35	0.45

ADL indicates activity of daily living; CCI, Charlson Comorbidity Index; CDPSM, Chronic Illness and Disability Payment System–Medicare; CMS-HCC, Centers for Medicare & Medicaid Services version of the Diagnostic Cost Group–Hierarchical Condition Category; RxHCC, Prescription Drug Hierarchical Condition Category.

^aAll models included the risk adjustment score as an independent variable along with demographic dummy variables for age (categorized as 65-69, 70-74, 75-79, 80-84, and 85+ years) and sex.

^bCount of ADL limitations was categorized as none, 1-2, 3-4, or 5-6.

^cPrior total expenditures were used in total expenditure models; prior drug expenditures were used in drug expenditure models.

■ **Table 4.** Predictive Ratios of Risk Adjustment Measures in Predicting Prescription Drug Expenditures

Risk Adjustment Measures ^a	Lowest Quartile	Second Lowest Quartile	Second Highest Quartile	Highest Quartile
Age and sex	6.95	1.74	0.99	0.46
Diagnosis-based measures				
CMS-HCC	6.93	1.71	1.01	0.46
CDPSM	6.88	1.71	1.02	0.47
CCI	6.87	1.70	1.01	0.47
RxHCC	6.17	1.61	1.06	0.52
Count of ADL limitations^b	7.00	1.74	0.99	0.46
Prior expenditures^c	4.03	1.38	1.05	0.71
Combined models				
CMS-HCC + count of ADL limitations	7.00	1.71	1.01	0.47
CDPSM + count of ADL limitations	6.91	1.71	1.02	0.47
CCI + count of ADL limitations	6.91	1.70	1.01	0.48
RxHCC + count of ADL limitations	6.22	1.61	1.06	0.52
Prior expenditures ^c + count of ADL limitations	4.05	1.38	1.05	0.71

ADL indicates activity of daily living; CCI, Charlson Comorbidity Index; CDPSM, Chronic Illness and Disability Payment System–Medicare; CMS-HCC, Centers for Medicare & Medicaid Services version of the Diagnostic Cost Group–Hierarchical Condition Category; RxHCC, Prescription Drug Hierarchical Condition Category.

^aAll models included the risk adjustment score as an independent variable along with demographic dummy variables for age (categorized as 65-69, 70-74, 75-79, 80-84, and 85+ years) and sex.

^bCount of ADL limitations was categorized as none, 1-2, 3-4, or 5-6.

^cPrior total expenditures were used in total expenditure models; prior drug expenditures were used in drug expenditure models.

Performance of Risk Adjustment Measures

served in a sample of elderly managed care beneficiaries in which the C statistics ranged between 0.65 and 0.69 in models given a highly stringent 1% high-cost threshold.¹¹

The inclusion of ADL limitations in a prospective payment system may reduce financial incentives for health plans to avoid enrollment of frail elderly patients, thus having positive spillover effects in terms of reducing Medicaid and institutional care expenditures.³ However, our data suggest that ADLs explained only 3% of the total expenditure variation and less than 1% of the drug expenditure variation. Information on functional status is not as readily available in claims data as it is in long-term-care settings, where it is routinely collected as part of the Minimum Data Set for nursing home resident assessment. The time and personnel costs of collecting and cleaning functional status data for community-dwelling beneficiaries may not be justified by the limited improvement in predictive power when combined with other risk adjustment measures.

Several limitations merit discussion. First, we used a multipronged case definition in the absence of a gold standard for identifying beneficiaries with ADRD. In related work, we found that an inclusive case definition resulted in less underestimation of ADRD prevalence and avoided sample selection bias due to relying on a single data source (eg, ADRD diagnosis).¹⁵ Second, institutionalized beneficiaries were excluded to provide a clearer picture of expenditure predictions among community residents. Many facility residents had supplemental health insurance; therefore, their claims data may have been incomplete. Third, the predictive performance and relative ranking of risk adjustment measures may be sensitive to regression model specification, especially in a small sample.⁹

To validate our findings, we used a GLM approach and found that the relative rankings of risk adjustment measures in the overall sample and by expenditure quartile were generally consistent with the OLS results. The magnitude of the predictive power and the predictive accuracy statistics in our analysis are similar to those reported by others.^{9,11,12} Given our limited sample size ($n = 1452$), it is possible that the goodness of fit and predictive accuracy are exaggerated due to overfit. Future research on larger samples would be useful to assess whether these results hold more generally. Finally, claims data

from Medicare fee-for-service enrollees rather than MA enrollees were used and Part D data were unavailable at the time of our analysis. Prescription drug utilization data recorded in the MCBS are based on self or proxy reports. We did not have ambulatory pharmacy claims data to determine whether pharmacy-based models (eg, RxRisk³⁹) would have improved predictive accuracy, especially in drug expenditure models.

Despite these limitations, this exploratory exercise sheds light on the challenges inherent in relating risk adjustment to expenditure prediction in subpopulations and provokes a useful policy debate about adding ADL limitations for payment setting. As healthcare expenditures continue to rise, Medicare and other payers will need reliable methods to predict expenditures accurately, particularly for chronically ill beneficiaries who incur persistently high expenditures. Additional research using actual MA and Part D data is needed to improve prospective payment methodology.¹⁹ With the introduction of new, expensive drugs and procedures, and the change in treatment patterns over time, it will be important to update risk adjustment measures for reimbursement purposes and to identify beneficiaries with high-cost risks for disease management, medication therapy management, and care coordination.

Table 5. Area Under the Receiver Operating Characteristic Curves^a in Prospective Expenditure Models

Risk Adjustment Measures ^b	Highest Spending 10%	
	Total Expenditures	Prescription Drug Expenditures
Age and sex	0.51	0.57
Diagnosis-based measures		
CMS-HCC	0.70	0.55
CDPSM	0.71	0.57
CCI	0.68	0.60
RxHCC	0.73	0.69
Count of ADL limitations^c	0.57	0.56
Prior expenditures^d	0.76	0.89
Combined models		
CMS-HCC + count of ADL limitations	0.72	0.55
CDPSM + count of ADL limitations	0.72	0.57
CCI + count of ADL limitations	0.70	0.60
RxHCC + count of ADL limitations	0.74	0.79
Prior expenditures ^d + count of ADL limitations	0.77	0.88

ADL indicates activity of daily living; CCI, Charlson Comorbidity Index; CDPSM, Chronic Illness and Disability Payment System–Medicare; CMS-HCC, Centers for Medicare & Medicaid Services version of the Diagnostic Cost Group–Hierarchical Condition Category; RxHCC, Prescription Drug Hierarchical Condition Category.

^aReported as C statistics.

^bAll models included age and sex.

^cCount of ADL limitations was categorized as none, 1-2, 3-4, or 5-6.

^dPrior total expenditures were used in total expenditure models; prior drug expenditures were used in drug expenditure models.

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