Measuring Pharmacy Performance in the Area of Medication Adherence: Addressing the Issue of Risk Adjustment

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ABSTRACT

BACKGROUND: Pharmacies and pharmacists play an important role in the health care system, improving health outcomes and enhancing quality through better pharmaceutical care. Yet, little information is available to accurately evaluate pharmacy store quality and thereby encourage quality improvement at the pharmacy store level.

OBJECTIVES: To (a) assess pharmacy performance in the area of medication adherence and (b) examine the impact of risk adjustment of performance scores on pharmacy rankings.

METHODS: We used proportion of days covered (PDC) to compute pharmacy performance scores using the 2007 Mississippi Medicare administrative claims dataset. We calculated unadjusted and adjusted quality scores for 685 pharmacies serving 137,497 eligible Medicare beneficiaries. Risk-adjusted quality scores were computed using a hierarchical logistic regression model (Method 1) and the shrinkage estimators of the model (Method 2). Patient demographics, income subsidy status, and comorbidity burden were used as variables for risk adjustment.

RESULTS: Unadjusted scores showed low levels of agreement (Cohen's kappa < 0.45) with risk-adjusted scores in identifying statistical outliers based on 95% CIs. Unadjusted scores also failed to identify 39%-43% of the top 20% and bottom 20% of pharmacies and displayed moderate agreement (0.4 < kappa < 0.5) with risk-adjusted scores. Pharmacy classifications based on risk-adjusted scores obtained from different statistical methods showed high levels of agreement (0.79 < kappa < 0.98).

CONCLUSIONS: In the risk-adjustment methods presented here, we account for many patient characteristics previously reported to be associated with medication adherence and available in our dataset. Risk-adjusted scores produced more robust indicators of pharmacy quality than unadjusted scores. Depending on the availability of important variables in the source data, the use of risk-adjusted quality indicators may lead to better evaluation of pharmacy quality and should be considered when providing public reports on pharmacy quality.

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What is already known about this subject

- Pharmacist-led interventions are successful in increasing medication adherence and thereby produce better outcomes, especially among elderly patients with chronic diseases.
- Pharmacy Quality Alliance's demonstration projects have successfully tested some pharmacy performance measures, including adherence-based measures.
- Studies on the predictors of medication adherence suggest a need to risk adjust for patient characteristics while computing adherence-based pharmacy quality scores.

What this study adds

- This study used Mississippi Medicare claims data and the proportion of days covered metric to measure pharmacy performance in the area of medication adherence.
- Our findings confirm that patient-level and pharmacy-level factors impact medication adherence and suggest that not adjusting for patient-level factors may lead to unreliable assessments of pharmacy quality.
- By comparing 2 approaches to address the issue of risk adjustment, we demonstrate that risk-adjusted scores produce more robust indicators of pharmacy quality than unadjusted scores, so use of risk-adjusted quality indicators may lead to better evaluation of pharmacy quality and should be considered when providing public reports on pharmacy quality.

Pharmacies and pharmacists play an important role in the health care system, improving health outcomes and enhancing quality through better pharmaceutical care.[1] Results from the FAME trial[2] and other systematic reviews in hypertension[3] and cardiovascular disease[4] indicate pharmacist-led interventions are successful in increasing medication adherence and improving quality of care, especially among elderly patients with chronic diseases. Many of these interventions tend to be complex and may include a combination of medication reminders, frequent patient education or counseling, use of improved administration systems such as blister packs, and use of medication event monitoring systems.[2-4] Apart from carrying out interventions directly targeted at improving medication adherence, pharmacists may also be required to conduct frequent comprehensive medication reviews for patients with multiple chronic illnesses to optimize therapy, decrease adverse events, and reduce pill burden, thereby improving medication adherence.[5] Yet, little information is available to accurately evaluate pharmacy store quality and thereby encourage quality improvement at the pharmacy store level. To address the measurement of pharmacy store quality, the Pharmacy Quality Alliance (PQA), in November

2006, developed measure concepts and initially worked with the National Committee for Quality Assurance to create technical specifications for these measure concepts.[6] These specifications have since been successfully tested and are currently owned and maintained by the PQA. In this study, we computed a pharmacy quality score in the area of medication adherence using technical specifications similar to the PQA specifications.

Researchers at RAND Health Corporation observed in a systematic review of the studies on barriers to medication adherence that, apart from costs and provider-related factors, patient characteristics such as diagnosis of depression and regimen complexity are among the most important barriers to medication adherence.[7] These findings and findings from other studies of the predictors of medication adherence[8-16] suggest a need to risk adjust for patient characteristics while computing adherence-based pharmacy quality scores. Failure to do so may result in comparisons that do not accurately reflect the effect of individual providers and rewards or penalties in pay-for-performance programs or other incentive/disincentive arrangements that may be reflective of the patient pool rather than pharmacy performance. Thus, we computed risk-adjusted scores on adherence-related pharmacy quality indicators using 2 different methodological approaches and compared pharmacy rankings based on these scores with rankings based on unadjusted scores.

Methods

A retrospective study was conducted using the 2007 Mississippi Medicare administrative claims dataset to compute and compare adjusted and unadjusted scores on adherence-based pharmacy quality indicators for pharmacies serving Medicare beneficiaries in the state.

Data Sources and Study Variables

Medicare data were made available in the form of Research Identifiable Files, which contain person-specific data on providers, beneficiaries, and recipients and includes individual identifiers such as age, date of birth, race, sex, and residence information. The de-identified form of these files, with an encrypted ID to link all records for patients on different files, was used. Use of these data files was covered by a data use agreement with the Centers for Medicare and Medicaid Services (CMS).

This study used the Beneficiary Summary file to retrieve demographic and eligibility information on patients. The claims files and MedPAR files helped identify patients who met inclusion criteria for the computation of the adherence-based performance measures. Further, the Part D Drug Event (PDE) file was used to compute these measures at a patient and pharmacy level. The PDE file was also used to measure a patient's comorbidity burden as determined by the Rx-Risk system. The Rx-Risk model, developed by Fishman et al. (2003),[17] identifies 29 chronic disease categories and specifies all the classes of medications that belong to each category. Patients were assigned to a chronic disease category if they filled a prescription for any medication in that chronic disease category during the measurement period. Patients could have been assigned to multiple categories based on their prescription fills in the measurement period. For each prescription record, the medication class was identified using the associated National Drug Code number and the AHFS (American Hospital Formulary Service) code. Approval from the Institutional Review Board of the University of Mississippi was obtained under the exempt category.

Pharmacy Quality Indicator Score

PQA developed a set of performance measures that could be widely implemented in the reporting and assessment of pharmacy quality. This study evaluated pharmacy performance on a subset of these measures in the area of medication adherence. The quantification of pharmacy performance was based on the technical specifications and implementation guidelines provided by PQA.

As a first step, medication adherence at the patient level was calculated, using the proportion of days covered (PDC) approach for these 7 therapeutic classes: beta blockers (BB), angiotensin-converting enzyme (ACE) inhibitors or angiotensin-receptor blockers (ARB), calcium channel blockers (CCB), biguanides, sulfonylureas, thiazolidinediones, and statins.

PDC is calculated as the proportion of days in the measurement period covered by prescription claims for a given medication or any other medication in that therapeutic category. Each patient's measurement period was identified as the period beginning on the date of the index prescription (first prescription in the calendar year) and ending on the date of disenrollment, death, the last day of the year, or the last day covered by the final prescription fill in the year if it was before the last date of the year. A PDC threshold of 0.8 (80%) was used to classify patients as "adherent" to that therapeutic class.

To have been eligible for measure computation, a patient must have filled at least 2 prescriptions for a medication or a combination medication in that therapeutic class (see Appendix for list of medications) on 2 unique dates of service in the measurement year. Additionally, consistent with PQA specifications, we required that a patient be aged 18 years or older as of the last day of the measurement year, be enrolled to receive pharmacy benefits, have no more than 1 gap of up to 45 days during the measurement year, and have had no nonacute stays in the measurement year.

If they received their prescriptions from multiple pharmacies, patients were attributed to the pharmacy that filled at least 75% of their prescriptions. Medication adherence was measured as a dichotomous outcome variable for 7 different therapeutic categories, and each patient could contribute multiple observations or opportunities, ranging from 1 to 7. For

example, a patient found to be eligible for inclusion in the computation of performance measures on Medication Adherence for Statins and Medication Adherence for Beta-Blockers would contribute 2 opportunities—1 for statins and 1 for BBs. Within each pharmacy, the number of opportunities that were fulfilled or that met the PDC threshold of 0.8 (measure numerator) was divided by the number of opportunities contributed by eligible patients (measure denominator) to arrive at the final pharmacy quality indicator score. Scores on pharmacy quality indicators were only calculated for pharmacies with at least 30 patients.[6]

It is important to note that, while based on PQA technical specifications, our definition of the final adherence pharmacy quality indicator score was slightly different from the definition currently suggested by PQA and used by CMS in their star-rating system. CMS currently measures pharmacy performance in the area of adherence using 3 indicators: Medication Adherence for Cholesterol (Statins), Medication Adherence for Hypertension (RAS antagonists), and Medication Adherence for Diabetes Medications. The quality indicator score on each of these indicators is reported separately and calculated as the number of eligible patients meeting a PDC threshold of 0.8 divided by the total number of eligible patients in the contract. In comparison, we computed a single, composite score of pharmacy performance by combining medication adherence rates for each patient in 7 different therapeutic categories.

Statistical Analysis

Unadjusted Pharmacy Quality Indicator Score. As already outlined, the unadjusted measure of pharmacy performance or unadjusted pharmacy quality indicator score was calculated as the proportion of eligible patients within each of the pharmacies who met the PDC threshold of 0.8. A 95% confidence interval (CI) for this measure was calculated using a normal approximation as:

$$O_j \pm 1.96 \times \sqrt{(O_j(1-O_j)/n_j)}$$

where O_j is the unadjusted quality indicator score for pharmacy j and n_j is the number of patients in pharmacy j.

The average unadjusted pharmacy quality indicator score was calculated as the sum of quality indicator scores of all pharmacies divided by the total number of pharmacies.

Risk Adjustment. A hierarchical logistic regression model with a random intercept was used to calculate risk-adjusted measures of pharmacy performance adjusted for patient case mix and opportunity mix. Adherence to medication was modeled as:

$$ln\left(\frac{p_{ij}}{1-p_{ij}}\right)=\alpha_j+\beta_1 x_{1ij}+\beta_2 x_{2ij} \ldots \ldots +\beta_k x_{kij}$$

where p_{ij} is the probability of being adherent for patient i in pharmacy j; β_k are model parameters; x_{kij} are values of variables being adjusted for including categorical variables for race, sex, and low-income subsidy status, continuous variables for age, and the average number of prescriptions per 30 days and dichotomous variables indicating the presence of each RxRisk category. We also needed to adjust for opportunity mix or the possibility that adherence rates may differ for each therapeutic category. This was done by including a categorical variable with 7 categories for the different therapeutic classes in the model.

This model accounts for the nesting of patients within a pharmacy by including an intercept term, α_j, that is different for each pharmacy. This intercept term is taken to be random and is expressed as a linear combination of the average intercept α and a group dependent deviation given by the random variable u_j. The random variable u_j was assumed to follow a normal distribution with mean of zero and variance of σ_u^2 and independent of the patient-level residuals:

$$\alpha_j=\alpha+u_j$$
$$u_j \sim N(0,\sigma_u^2)$$

The pharmacy-specific intercepts provide a measure of the effect of the pharmacy on adherence controlling for all other variables in the model. Additionally, the residual intraclass correlation coefficient was computed to provide a measure of variation between pharmacies. The residual intraclass correlation coefficient is a measure of the correlation between 2 individuals chosen at random from any random pharmacy. It translates to the proportion of the unexplained variation after controlling for the effect for the explanatory variables that can be attributed to variation at the pharmacy level (or group membership). The observation-level residuals follow a logistic distribution that implies a fixed variance of $\pi^2/3$. The intraclass correlation coefficient for the random-intercept model was estimated as suggested by Snijders and Bosker (1999)[18] as:

$$\rho=\frac{\sigma_u^2}{\sigma_u^2+\pi^2/_3}$$

where ρ is the intraclass coefficient, σ_u^2 is the variance of the random part of the pharmacy specific intercepts, and $\pi^2/_3$ is the variance of patient-level residuals.

Risk-Adjusted Scores. As mentioned earlier, 2 statistical approaches or methods were used to calculate risk-adjusted pharmacy quality indicator scores. These are detailed below.

Method 1

For a given pharmacy, the expected quality indicator score was calculated as the average of the individual predicted probabilities of adherence within that pharmacy based on the hierarchical logistic regression model.

$$E_j = \frac{1}{n_j} \times \sum_{i=1}^{n_j} \hat{p}_{ij}$$

where E_j is the expected quality indicator score for pharmacy j, $\hat{p}_{ij}$ is the predicted probability of adherence for patient i, and n_j is the number of patients at pharmacy j.

The risk-adjusted quality indicator score for each pharmacy was then calculated as the ratio of observed (or unadjusted) quality indicator score to the expected quality indicator score for that pharmacy, multiplied by the average unadjusted pharmacy quality score:

$$(O_j/E_j) \times (\sum_{j=1}^{N} O_j)/N$$

where N is the total number of pharmacies in the data.

To identify outlier pharmacies, the 95% CIs of the risk-adjusted score was calculated (as suggested by Hosmer and Lemeshow 1995),[19] as:

$$\frac{O_j \pm 1.96 \times \frac{\sqrt{\sum_{i=1}^{n_j} \hat{p}_{ij}(1-\hat{p}_{ij})}}{n_j}}{E_j} * (\sum_{j=1}^{N} O_j)/N$$

Method 2

As mentioned earlier, the pharmacy specific intercepts provide a measure of the effect of the pharmacy after accounting for the patient-level explanatory variables. Specifically, the exponentiation of the random variable, $exp(u_j)$, is equal to the ratio of the odds of adherence at pharmacy j to the odds of adherence at the average pharmacy controlling for patient characteristics.[20] This method uses the exponentiation of the random variable u_j (or shrinkage estimator u_j) multiplied by the odds of the average unadjusted pharmacy quality score as a risk-adjusted measure of pharmacy performance. The 95% CI of this risk-adjusted measure was calculated using the 95% CI of u_j.

Comparison of Unadjusted and Adjusted Scores. Based on their quality indicator scores, pharmacies were classified as low-quality outliers, medium-quality pharmacies, and high-quality outliers.

As done by Li et al. (2009),[21] pharmacies were classified as low-quality outliers if their unadjusted scores were less than the average unadjusted score and the 95% CIs of their unadjusted scores did not contain the average unadjusted score. Pharmacies were classified as high-quality outliers if their unadjusted scores were higher than the average unadjusted score and the 95% CIs of their unadjusted scores did not contain the average unadjusted score. Pharmacies were classified as medium-quality if the 95% CIs of their unadjusted scores contained the average unadjusted score. Similarly, pharmacies were also classified as low-, medium-, or high-quality outliers based on the 95% CIs of their risk-adjusted scores obtained from Method 1 and Method 2.

The agreement in pharmacy classification based on unadjusted and adjusted scores obtained from the different methods previously detailed was evaluated using Cohen's weighted kappa (κ) coefficient.[22]

Further, agreement in the identification of high-, medium-, and low-quality pharmacies, defined as the top 20%, the middle 60%, and the bottom 20% of the distribution using unadjusted and adjusted scores, was also evaluated.

As mentioned earlier, this study involved the analysis of observations that were nested within patients (i.e., for individuals who consumed medications in more than 1 of the 7 classes) who were in turn nested within pharmacies. So, we also explored the option of using a 3-level logistic regression model to calculate risk-adjusted scores. In doing so, we accounted for nesting of observations within patients by specifying a model with a compound symmetric structure for the variance-covariance matrix of the residuals for all the patients. This structure assumes a homogenous variance and homogenous covariance of the residuals. In other words, observations within each patient had the same variance, and the correlation between any 2 observations of a patient was the same. The model with a compound symmetry structure of the error variance-covariance matrix is equivalent to a model with a patient-specific random intercept component and produces similar results to that obtained by adding a patient-level random intercept to the 2-level model. We compared the classification of pharmacies obtained from the risk-adjusted scores using this model with that obtained from the risk-adjusted scores using the 2-level model and the unadjusted scores.

All analyses were conducted using SAS version 9.2 (SAS Institute, Inc., Cary, NC). The GLIMMIX procedure in SAS was used to estimate the hierarchical logistic regression models.

Results

A total of 137,497 Medicare beneficiaries who met eligibility criteria contributed 285,388 observations or medication adherence opportunities. Patients were attributed to a total of 685 pharmacies in the state for which quality indicator scores were computed.

Table 1 shows the distribution of various patient characteristics in the sample and the odds ratio estimate for each patient characteristic variable in the 2-level random-intercept risk-adjustment model that was used to compute Method 1 risk-adjusted scores. Patient characteristics such as age, race, sex, low-income subsidy status, and average number of prescriptions per month were all found to be significant determinants of fulfillment of medication adherence opportunities. The presence of most medical conditions, as measured by the RxRisk classification system, was associated with significantly lesser odds of fulfillment of medication adherence opportunities.

The c-statistic of the 2-level model was estimated to be 0.73. The pharmacy-level variance component was estimated to be 0.043 with a standard error of 0.003. Nonzero covariance parameters (or presence of a random effect) was confirmed using a Wald test ($P<0.0001$). The residual intraclass correlation coefficient (ρ) for the random intercept model was

TABLE 1 Prevalence of Patient Characteristics in the Eligible Population and Odds Ratio Estimate of Patient Characteristic Variables in Random-Intercept Regression Model Used to Produce Method 1 Risk-Adjusted Scores

Patient Characteristics	Prevalence (%) or Mean±SD	Point Estimate	*P* Value
RxRisk category			
Anxiety and tension	11.98	0.675	<0.0001
Asthma	21.00	0.663	<0.0001
Bipolar disorder	0.30	0.964	0.6860
Cardiac disease	8.53	0.557	<0.0001
Vascular disease	9.80	0.762	<0.0001
Cystic fibrosis	0.07	0.408	<0.0001
Depression	27.57	0.641	<0.0001
Diabetes	29.51	0.671	<0.0001
Hypertension	47.38	0.643	<0.0001
Epilepsy	14.75	0.672	<0.0001
ESRD	0.17	0.731	0.0018
Gastric acid disorder	32.71	0.668	<0.0001
Gout	6.08	0.716	<0.0001
AIDS	2.56	0.922	0.0046
Hyperlipidemia	43.43	0.784	
Inflammatory bowel disorder	10.59	0.767	<0.0001
Liver disease	1.50	0.695	<0.0001
Malignancies	9.73	0.765	<0.0001
Parkinson's disease	3.81	0.721	<0.0001
Psychotic illness	6.30	0.770	<0.0001
Renal disease	0.26	0.610	<0.0001
Rheumatoid arthritis	14.70	1.048	0.0151
Thyroid disorder	14.04	0.764	<0.0001
Transplant	0.27	0.777	0.0046
Tuberculosis	0.29	0.727	<0.0001
Pain	43.15	0.663	<0.0001
Pain and inflammation	25.47	0.865	<0.0001
Glaucoma	8.84	0.860	<0.0001
Race			<0.0001
White	62.53	Reference	
Black	36.81	0.636	
North American Native	0.16	0.481	
Unknown race	0.05	0.497	
Other	0.20	0.814	
Asian	0.18	0.620	
Hispanic	0.06	0.584	
Sex			<0.0001
Female	65.36	Reference	
Male	34.64	1.020	
Age	70.85±11.73	1.012	<0.0001
Cost share group[a]			<0.0001
No premium subsidy	46.02	Reference	
Subsidy group 1	3.39	1.327	
Subsidy group 2	48.58	1.020	
Subsidy group 3	2.01	1.038	
Prescriptions per month	4.96±3.00	1.457	

[a]*Subsidy group 1 consisted of beneficiaries with 100% premium-subsidy and no copayment. Subsidy group 2 consisted of beneficiaries with 100% premium-subsidy and low copayment/high copayment and beneficiaries with a low-income subsidy, a 100% premium-subsidy, and high copayment. Subsidy group 3 consisted of beneficiaries with low-income subsidy, 15% copayment, and 25%-100% premium-subsidy.*

AIDS = acquired immunodeficiency syndrome; ESRD = end-stage renal disease; SD = standard deviation.

estimated to be 0.013, which indicates that 1.3% of the unexplained variation, after controlling for patient characteristics, could be attributed to variation between pharmacies. This further reduced to 0.8% in the 3-level model accounting for correlation of observations within patients, with a pharmacy-level variance component of 0.026 (standard error of 0.003).

Table 2 shows the agreement between the unadjusted quality indicator scores and the risk-adjusted quality indicator scores in identifying outliers. Low-quality outliers and high-quality outliers were determined on the basis of the 95% CI of the unadjusted and adjusted quality scores. Pharmacies of medium quality are those whose quality scores are not significantly different from the average quality score in the sample. Agreement in pharmacy classification was moderate when risk adjustment was done using a random intercept model (Method 1; $\kappa = 0.43$; 95% CI = 0.37-0.50) and further reduced when the shrinkage estimators of the random intercept model (Method 2) were used ($\kappa = 0.39$; 95% CI = 0.32-0.45). The 2 risk-adjustment methods showed substantial agreement in identifying quality outliers ($\kappa = 0.79$; 95% CI = 0.73-0.84).

Agreement of unadjusted and risk-adjusted pharmacy quality indicator scores in identifying the top 20% and bottom 20% of all pharmacies is presented in Table 3. Cohen's kappa values evaluating the comparison of unadjusted and risk-adjusted scores were similar for the 2 methods of risk-adjustment used. Unadjusted scores showed moderate agreement with the risk-adjusted scores. However, almost perfect agreement ($\kappa = 0.88$; 95% CI = 0.84-0.91) was observed between the 2 methods in the identification of the top 20% and the bottom 20% performers.

When a 3-level model was used to risk-adjust scores, we obtained a similar classification of pharmacies. A comparison of the classification of pharmacies as top 20%, middle 60%, and bottom 20% obtained from the 3-level model and the 2-level model yielded a Cohen's kappa of 0.97 (95% CI = 0.96-0.98) when Method 1 was used and 0.88 (95% CI = 0.84-0.91) when Method 2 was used.

Discussion

As health care in the United States moves to a value-driven model, there is an increased emphasis being placed on the measurement of quality of the service provided. Reports comparing the quality of hospitals,[23] nursing homes,[24] and other institutional providers have been made available on a public domain by CMS and The Joint Commission. CMS also tracks and reports performance of Medicare Part D plans in 4 different domains using a star-rating system.[25] The measures used to evaluate drug plans in the domain of patient safety include 3 measures in the area of medication adherence calculated from claims data using the PDC metric.[25] With the star-ratings program providing incentives for the high-performing plans, the demand for pharmacy quality measures, especially in areas shown to be effected by pharmacy services (most importantly

TABLE 2 Agreement in Identifying Pharmacy Quality Outliers—Using 95% CI of Quality Scores: Comparison of Outlier Status of Pharmacies Based on Unadjusted and Risk-Adjusted Pharmacy Quality Indicator Scores

	Outlier Status Based on Risk-Adjusted Scores					
	Method 1[a] (n = 685)			Method 2[b] (n = 685)		
Outlier Status Based on Unadjusted Scores	Low-Quality Outlier	Not Outlier	High-Quality Outlier	Low-Quality Outlier	Not Outlier	High-Quality Outlier
Low-quality outlier (n)	54	77	3	44	88	2
Not outlier (n)	32	385	15	17	409	6
High-quality outlier (n)	4	63	52	1	80	38
Change in classification (%)[c]	40	26.7	25.7	29	29.1	17.4
Weighted κ (95% CI)[d]	0.43 (0.37-0.50)			0.39 (0.32-0.45)		

[a]*Based on random-intercept model.*
[b]*Based on shrinkage estimators of random-intercept model.*
[c]*Change in classification was calculated for each risk-adjustment method using the classification based on the risk-adjustment method as the initial classification.*
[d]*Cohen's weighted kappa coefficient is a measure of agreement between unadjusted performance ratings and ratings based on the risk-adjustment method with higher values indicating greater agreement.*
CI = confidence interval.

medication adherence),[26-28] is likely to become greater. Indeed, Inland Empire Health Plan (IEHP) recently announced 1 of the first large-scale pay-for-performance programs for community pharmacies in the country.[29] In its announcement, IEHP states that PQA metrics endorsed and currently used by CMS in the star-rating program, including the PDC metric in the domain of adherence, will be used to assess pharmacy performance with a goal of defining a payment model for pharmacy services.[29] Since PQA's phase I demonstration projects have successfully tested some pharmacy performance measures, including the PDC metric, such measures are likely to be implemented widely soon.[30] In this study, we used Mississippi Medicare claims data and the PDC metric to measure pharmacy performance in the area of medication adherence and compared 2 approaches to address the issue of risk adjustment—the use of a random intercept logistic regression model and the shrinkage estimators of the random intercept model.

In order to have a valid risk-adjustment method, it is necessary that the patient characteristics adjusted for have an influence on the patient outcome used as a measure of facility quality of care. The hierarchical logistic regression models used included measures of patient comorbidity, socioeconomic status, and demographics as determinants of adherence. The models displayed good predictive ability (c-statistics > 0.7) for medication adherence, thereby justifying the choice of patient characteristics to be adjusted for when measuring pharmacy quality. The residual intraclass correlation coefficient for the models with and without an adjustment for correlation of observations at the patient level was 0.008 and 0.013, respectively. These findings suggest that, although pharmacy-level factors have a significant impact, not adjusting for patient-level factors may lead to unreliable assessments of pharmacy quality.

It was seen that the classification of pharmacies as low- or high-quality outliers changed substantially after quality scores were risk adjusted. Approximately 26% of the high-quality outliers and 40% of the low-quality outliers, as identified using Method 1 risk-adjusted scores, changed their classification when unadjusted scores were used. Further, 27% of the medium quality or nonoutlier pharmacies were classified as being outliers by unadjusted scores. Comparing unadjusted scores to Method 2 risk-adjusted scores, we found that 28.3% of all pharmacies changed their classification. The weighted kappa coefficient indicated a fair-to-moderate agreement between unadjusted and risk-adjusted scores. The lack of agreement between unadjusted and risk-adjusted rankings has been demonstrated for other quality measures. Li et al.[21] studied the impact of different statistical methodologies in risk adjusting quality measures (QMs) of the nursing home quality report cards published by CMS. They reported an overall kappa of 0.59-0.76 for the agreement between unadjusted and risk-adjusted measures in identifying quality outliers using the 95% CIs of QMs.

CMS currently rewards the top 20% of hospitals as a part of its Premier Hospital Quality Incentive Demonstration program.[31] The top 10% receive an incentive of 2% and the next 10% receive an incentive of 1% bonus payment per Medicare patient along with their regular Medicare prospective payments.[31] This structure is also used by CMS for a pay-for-performance demonstration program for nursing homes.[21] We examined the effect of case-mix adjustment of pharmacy quality measures on identification of pharmacies eligible for a reward if such a program were to be implemented for pharmacies serving Medicare beneficiaries. Once again, there was only moderate agreement between unadjusted and

TABLE 3 Agreement in Identifying Pharmacy Quality Outliers—Using Top 20% and Bottom 20%: Comparison of Classification of Pharmacies Based on Unadjusted and Risk-Adjusted Pharmacy Quality Indicator Scores

Classification Based on Unadjusted Scores	Classification Based on Risk-Adjusted Scores					
	Method 1[a] (n = 685)			Method 2[b] (n = 685)		
	Bottom 20%	Middle 60%	Top 20%	Bottom 20%	Middle 60%	Top 20%
Bottom 20% (n)	79	58	2	76	61	0
Middle 60% (n)	53	303	52	55	302	54
Top 20% (n)	5	50	83	6	48	83
Change in classification (%)[c]	42.3	25.6	39.4	44.5	26.5	39.4
Weighted κ (95% CI)[d]	0.49 (0.43-0.55)			0.47 (0.42-0.53)		

[a]*Based on random-intercept model.*
[b]*Based on shrinkage estimators of random-intercept model.*
[c]*Change in classification was calculated for each risk-adjustment method using the classification based on the risk-adjustment method as the initial classification.*
[d]*Overall kappa coefficient is a measure of agreement between unadjusted performance ratings and ratings based on the risk-adjustment method with higher values indicating greater agreement.*
CI = confidence interval.

risk-adjusted pharmacy classifications. Unadjusted scores classified 58 (42.3%) of the low-performing pharmacies, identified by Method 1 risk-adjusted scores, as not being in the bottom 20% and failed to identify 54 (39.4%) pharmacies in the high performing category (top 20%). When we compared the classification based on unadjusted score with that based on Method 2 risk-adjusted scores, we found that 32.7% of all pharmacies changed their classifications, which included 44.5% of the low-performing pharmacies (bottom 20%) and 39.4% of the high-performing pharmacies (top 20%). Similar results were observed when a 3-level model was specified with 32% and 33.6% of all pharmacies changing classifications when unadjusted scores were compared with Method 1 and Method 2 risk-adjusted scores, respectively.

In our study, the pharmacy rankings based on the different risk-adjustment methods showed a high level of agreement with each other. A comparison of the 2 risk-adjustment methods in the classification of outlier pharmacies yielded a kappa of 0.79 (95% CI = 0.73-0.84). Further, a comparison of the 2 risk-adjustment methods in the identification of the top 20% and bottom 20% yielded a kappa of 0.88 (95% CI = 0.84-0.91). These results suggest that the risk-adjusted measures, despite the statistical methodology used, provide a more robust and more useful assessment of pharmacies than the corresponding unadjusted measure.

Method 2 classified fewer pharmacies as outliers (i.e., low or high; see Table 2). This method results in the shrinkage of performance scores of facilities with smaller sample sizes to an estimate closer to the average performance in the entire population, thereby producing fewer outliers. For this reason, and its difficulty in interpretation, Mukamel et al. (2010)[32] caution against the use of this method for producing risk-adjusted measures to rank providers for quality report cards.

As noted earlier, CMS currently measures pharmacy performance in the domain of adherence using 3 separate indicators: Medication Adherence for Cholesterol (Statins), Medication Adherence for Hypertension (RAS antagonists), and Medication Adherence for Diabetes Medications.[25] In comparison, in this study we defined unique combinations of patients and therapeutic categories as opportunities and calculated a composite pharmacy quality indicator score for each pharmacy as the number of opportunities that were fulfilled or that met the PDC threshold of 0.8 within that pharmacy. However, in an earlier analysis of the impact of risk adjustment using separate pharmacy quality indicators for each therapeutic category, we obtained results similar to the results reported in the present study, with 29%-39% of the high-performing pharmacies (top 20%), as identified by the Method 1 and Method 2 risk-adjusted scores, being misclassified.[33] Among the quality indicators currently used by CMS, misclassification of high-performing pharmacies was 34.1% for the Medication Adherence for Hypertension (ACEI/ARB) quality indicator and the Medication Adherence for Cholesterol (Statins) quality indicator when Method 1 was used to produce risk-adjusted scores.[33] We chose not to report these results in detail here to keep the focus on the main goal of this study, which was to illustrate the need for risk adjustment in pharmacy performance assessment in the area of medication adherence and present a robust method of calculating risk-adjusted scores irrespective of the use of many therapeutic area-specific quality indicators or 1 composite quality indicator.

As shown here, not adequately addressing the effects of patient case mix while measuring quality could lead to misclassification of pharmacies. Similar results were reported in studies examining the effect of risk adjustment on New York State and Massachusetts Cardiac Surgery Report cards,[34,35]

hospital rankings,[36] and Nursing Home Compare report cards.[37,38] These studies demonstrate that unadjusted quality measures will reward facilities with the healthiest patient case mix rather than the best performers. Also, this would unjustly penalize facilities serving sicker patients, minority groups, and those in lower socioeconomic strata. In a recently published study, Young et al. (2014)[39] found that around 45%-50% of Medicare Part D contracts moved up or down a star in the CMS star-rating system in the domain of medication adherence after adjusting performance scores for socioeconomic characteristics of contract enrollees, suggesting that CMS should consider case-mix adjustment of these scores. While the study by Young et al. was at the contract level and the present study is at the pharmacy level, both studies support the importance of adjusting for patient case mix while assessing performance in the area of medication adherence. Not doing so could ultimately lead to health care facilities engaging in "cream skimming" or avoiding the sickest patients because of their concern about their rankings as evidenced by studies examining the effects of public reporting of physician performance and nursing home performance.[40,41] In a recent communication, CMS acknowledged they "rely on consensus based organizations' decisions about whether a measure should or should not be case-mix adjusted."[42] In response to this communication, PQA indicated it will be exploring the need for case-mix adjustment in the measures it has developed and is developing at this time.[43]

It is worth reiterating that our study was carried out using 2007 Mississippi Medicare Claims data. Since there have been changes with respect to the evaluation of quality of medication use systems implemented by CMS since then, such as the star-rating system, one might expect to see differences in the distribution of pharmacy performance scores if newer data were used. Specifically, Medicare Part D plans may have begun to place a greater emphasis on performance in the adherence metrics discussed here leading to higher scores on average. However, it is unlikely that these changes intended to affect performance at the plan level would have affected the distribution of pharmacies with respect to rankings or outlier status that were used in this study to determine the impact of risk adjustment.

Limitations

Like other studies using claims data, a limitation of this study is the use of the PDC metric, which may not be an accurate measure of patient medication adherence. Another important limitation of this study, and most studies on methods of case-mix adjustment of quality measures, is that there are no true or real quality rankings that can be used to compare the performance of the risk-adjustment methods. In the risk-adjustment methods presented here, we account for many patient characteristics previously reported to be associated with medication adherence and available in our dataset. There may be other demographic predictors that were not available in our dataset and are usually not available in administrative claims data whose inclusion in the models could have provided a more comprehensive risk-adjustment method. Indeed, the use of risk-adjusted scores for pharmacy quality assessment depends on the availability of the variables in the source data and may not be practical for all applications. It is also important to note that defining the ideal pharmacy quality indicator was not one of the objectives of this study and that there may be a difference in the definition of pharmacy quality indicator used in this study and the definition currently being used by some health plans, government agencies such as CMS, pharmacy benefit managers, and pharmacies.

Conclusions

The results of the present study highlight the need for risk adjustment in assessing performance in the domain of medication adherence. We show that not adjusting for patient case-mix might penalize some truly high-performing community pharmacies serving a sicker population, while rewarding some community pharmacies serving a healthier population if a pay-for-performance program similar to that announced by IEHP were to be implemented. Additionally, we demonstrate that risk-adjusted scores produce more robust indicators of pharmacy quality than unadjusted scores, indicating that the use of risk-adjusted quality indicators may lead to better evaluation of pharmacy quality and should be considered when providing public reports on pharmacy quality and when implementing pay-for-performance initiatives for community pharmacies. While this study concentrated on pharmacy performance in the area of medication adherence, future research should address the issue of risk adjustment of pharmacy performance measures in other areas and thereby concentrate on refining the way pharmacies are assessed to produce a fair and just method of evaluating pharmacy service.

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DISCLOSURES

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APPENDIX List of Medications

Beta Blocker Medications (BB)

BB medications

- acebutolol HCL
- atenolol
- betaxolol HCL
- bisoprolol fumarate
- carteolol HCL
- carvedilol
- labetalol HCL
- metoprolol succinate
- metoprolol tartrate
- nadolol
- nebivolol HCL
- penbutolol sulfate
- pindolol
- propranolol HCL
- timolol maleate

BB combination products

- atenolol & chlorthalidone
- bisoprolol & HCTZ
- nadolol & bendroflumethiazide
- metoprolol & HCTZ
- propranolol & HCTZ
- timolol & HCTZ

Note: Active ingredients are limited to oral formulations only. Excludes the BB sotalol because it is indicated for the treatment of ventricular arrhythmias (and not for hypertension).
HCL = hydrochloride; HCTZ = hydrochlorothiazide.

Angiotensin-Converting Enzyme (ACE) Inhibitors or Angiotensin-Receptor Blockers (ARB)

ARB medications

- candesartan
- eprosartan
- irbesartan
- losartan
- olmesartan
- telmisartan
- valsartan

ACE inhibitor medications

- benazepril
- captopril
- enalapril
- fosinopril
- lisinopril
- moexipril
- perindopril
- quinapril
- ramipril
- trandolopril

ACE inhibitor combination products

- amlodipine & benazepril
- benazepril & HCTZ
- captopril & HCTZ
- enalapril & HCTZ
- enalapril & felodipine
- fosinopril & HCTZ
- lisinopril & HCTZ
- moexipril & HCTZ
- lisinopril & nutritional supplement
- quinapril & HCTZ
- trandolopril-verapamil HCL

ARB combination products

- candesartan & HCTZ
- eprosartan & HCTZ
- telmisartan & amlodipine
- irbesartan & HCTZ
- losartan & HCTZ
- amlodipine & olmesartan
- olmesartan & HCTZ
- telmisartan & HCTZ
- aliskiren & valsartan
- valsartan & HCTZ
- amlodipine & valsartan
- amlodipine & valsartan & HCTZ

Note: Active ingredients are limited to oral formulations only.
HCL = hydrochloride; HCTZ = hydrochlorothiazide.

Calcium Channel Blockers (CCB)

CCB medications

- amlodipine besylate
- diltiazem HCL
- felodipine
- isradipine
- nicardipine HCL
- nifedipine (long acting only)
- verapamil HCL
- nisoldipine

CCB combination products

- amlodipine besylate & benazepril HCL
- amlodipine & valsartan
- amlodipine & valsartan & HCTZ
- enalapril maleate & felodipine
- telmisartan & amlodipine
- amlodipine & olmesartan
- trandolopril & verapamil HCL
- amlodipine & atorvastatin

Note: Active ingredients are limited to oral formulations only. Excludes CCB nimodipine, since it has a limited indication for use following a subarachnoid hemorrhage.
HCL = hydrochloride; HCTZ = hydrochlorothiazide.

APPENDIX List of Medications *(continued)*

Biguanide Medications			
Biguanides			
•metformin			
Biguanide & sulfonylurea combination products			
• glipizide & metformin	• glyburide & metformin		
Biguanide & thiazolinedione combination products			
• rosiglitazone & metformin	• pioglitazone & metformin		
Biguanide & meglitinide combinations			
•repaglinide & metformin			
Biguanide & DPP-IV inhibitor combinations			
•sitagliptin & metformin			
Note: Active ingredients are limited to oral formulations only (includes all dosage forms).			
Sulfonylurea Medications			
Sulfonylureas			
• acetohexamide • chlorpropamide • glipizide • glyburide	• glimepiride • tolazamide • tolbutamide		
Sulfonylurea & biguanide combination products			
• glipizide & metformin	• glyburide & metformin		
Sulfonylurea & thiazolidinedione combination products			
• rosiglitazone & glimepiride	• pioglitazone & glimepiride		
Note: Active ingredients are limited to oral formulations only (includes all salts and dosage forms).			
Thiazolidinedione Medications			
Thiazolidinediones			
•pioglitazone	• rosiglitazone		
Thiazolinedione & biguanide combination products			
•rosiglitazone & metformin	• pioglitazone & metformin		
Thiazolidinedione & sulfonylurea combination products			
•rosiglitazone & glimepiride	• pioglitazone & glimepiride		
Note: Active ingredients are limited to oral formulations only (includes all dosage forms).			
Statin Medications			
Statins			
• lovastatin • rosuvastatin	• fluvastatin • atorvastatin	• pravastatin	• simvastatin
Statin combination products			
• niacin & lovastatin • atorvastatin & amlodipine	• niacin & simvastatin	• pravastatin & aspirin	• ezetimibe & simvastatin
Note: The active ingredients are limited to oral formulations only (includes all dosage forms).			