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Regional Variation in Use of a New Class of Antidiabetic Medication Among Medicare Beneficiaries: The Case of Incretin Mimetics

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Abstract

Background—When incretin mimetic (IM) medications were introduced in 2005, their effectiveness compared other less-expensive second-line diabetes therapies was unknown, especially for older adults. Physicians likely had uncertainty about the role of IMs in the diabetes treatment armamentarium. Regional variation in uptake of IMs may be marker of such uncertainty.

Objective—To investigate the extent of regional variation in the use of IMs among beneficiaries and estimate the cost implications for Medicare.

Methods—This was a cross-sectional analysis of 2009–2010 claims from a nationally representative sample of 238 499 Medicare Part D beneficiaries aged ≥ 65 years, who were continuously enrolled in fee-for-service Medicare and Part D and filled ≥ 1 antidiabetic prescription. Beneficiaries were assigned to 1 306 hospital-referral regions (HRRs) using ZIP codes. The main outcome was adjusted proportion of antidiabetic users an HRR receiving an IM.

Results—Overall, 29 933 beneficiaries (12.6%) filled an IM prescription, including 26 939 (11.1%) for sitagliptin or saxagliptin and 3718 (1.6%) for exenatide or liraglutide. The adjusted proportion of beneficiaries using varied more than 3-fold across HRRs, from 5th and 95th percentiles of 5.2% to 17.0%. Compared with non-IM users, users faced a 155% higher annual Part D plan (\$1067 vs \$418) and 144% higher patient (\$369 vs \$151) costs for antidiabetic prescriptions.

Conclusion—Among older Part D beneficiaries using antidiabetic drugs, substantial regional variation in the use of IMs, not accounted for by sociodemographics and health status. IM use was associated with substantially greater costs for Part D plans and beneficiaries.

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Declaration of Conflicting Interests

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Keywords

Medicare; diabetes; pharmacoepidemiology; regional variation

Introduction

Diabetes currently affects 1 out of every 4 Americans 65 years and older and accounts for 32% of total Medicare expenditures. Optimizing antidiabetic drug use is thus of critical importance for Medicare.¹ Although metformin is widely accepted as the first-line therapeutic agent according to current clinical guidelines, there is a lack of direct comparative effectiveness data and no consensus in diabetes treatment guidelines regarding the optimal agent to add if metformin monotherapy fails to adequately control blood glucose.² As a result, providers may be uncertain as to how to choose among the remaining therapeutic subclasses of antidiabetic agents and, in particular, when to use agents that have been introduced to the market more recently, such as incretin mimetics (IMs).³

IMs include both dipeptidyl peptidase-4 (DPP-4) inhibitors and glucagon-like peptide-1 agonists, with the first agent from this class—exenatide—gaining approval in 2005 and subsequent agents being approved in 2006 (sitagliptin), 2009 (saxagliptin), 2010 (liraglutide), 2011 (linagliptin), and 2013 (alogliptin).⁴ The IMs were initially heralded as therapeutic breakthroughs, with comparable efficacy in lowering hemoglobin A_{1C}, low risk of hypoglycemia, and lack of associated weight gain compared with other established and commonly used second-line therapies (eg, sulfonylureas, thiazolidinediones [TZDs], and insulin).⁴ However, concern about adverse events, most notably deleterious pancreatic effects, has been raised since their introduction to the market.^{5–7}

Given the uncertainty regarding their role as a second-line diabetes therapy, the substantially greater cost of IMs compared with established second-line agents has major implications for both patients and payers. In fact, substantial variation in the use of new brand drugs in other therapeutic categories is the main contributor to regional variation in prescription spending in Medicare⁸ and is also an important source of potential excess spending.⁹ Moreover, although 4 decades of research have revealed regional variation in health care use, there are a limited number of studies examining regional variation in prescription medication use.¹⁰

To better understand the use of this new antidiabetic drug class, we examined regional variation in the use of IMs in Medicare Part D. First, we examined the patient and provider-level characteristics associated with the use of these medications. Second, we estimated differences in Medicare and beneficiary spending on diabetes medications among IM and non-IM users. To compare variation of IMs with that of other diabetes medication classes, we also examined regional variation in the 3 most common oral antidiabetic drug subclasses—metformin, sulfonylureas, and TZDs.

Methods

Data Sources and Sample

We obtained 2009–2010 Medicare claims (Parts A, B, and D) and enrollment data for individuals in the Chronic Conditions Warehouse (CCW) 10% random sample of all Part D beneficiaries who were continuously enrolled in a stand-alone prescription drug plan and alive in 2009 ($n = 1\,529\,825$). For this sample, we obtained the Part D Prescription Drug Event (PDE) file, which contains information on each prescription fill by beneficiaries in the sample, including drug name, fill date, quantity, and an encrypted prescriber identifier. The Prescriber Characteristics file was linked to the PDE file via the prescriber identifier to obtain information on prescriber specialty. We used the beneficiary summary files to identify demographic information, along with the CCW condition indicators and inpatient, outpatient, and carrier files to describe health status. We included beneficiaries in this study if they were ≥ 65 years of age on January 1, 2009, continuously enrolled for both years (2009–2010), and filled ≥ 1 prescription for an antidiabetic medication (appendix) during either 2009 or 2010. Of note, antidiabetic drugs are not routinely prescribed for nondiabetes indications in older adults, and the overwhelming majority of our sample also had a CCW diabetes flag (98.7%), giving us confidence that we did not misclassify antidiabetic medication users. The University of Pittsburgh Institutional Review Board deemed the study exempt.

Measures of Antidiabetic Prescription Use

On the basis of ZIP code of residence, beneficiaries were assigned to 1 of 306 hospital-referral regions (HRRs; range of beneficiaries per HRR: 66–8206) described in the Dartmouth Atlas of Health Care.¹¹ Our main outcome was the proportion of beneficiaries in a HRR receiving an IM among those receiving any antidiabetic drug during the study period. IM use was first measured at the beneficiary level, and the main outcome was then constructed by aggregating IM use at the HRR level. The IMs assessed were those available in the United States during the study years, including exenatide, sitagliptin, saxagliptin, and liraglutide. Prescriptions for combination drugs (eg, sitagliptin/metformin) were attributed to each drug in the combination and each class to which those drugs belonged. To allow for a comparison of any variation in IM use detected with variation in other classes, we assessed regional variation in the 3 most common oral antidiabetic drug classes—metformin, sulfonylureas, and TZDs.

Beneficiary and Part D Plan Prescription Drug Costs for Antidiabetic Drugs

The Part D PDE file includes the amount paid to the pharmacy by the prescription drug plan and the beneficiary. As such, we measured individual-level and plan-level annual prescription drug expenditures for antidiabetic medications among those with and without IM use over the 2 years. In addition, we assessed whether HRRs with higher IM use were similar to those HRRs with overall higher spending for all drugs and those HRRs with greater brand-name drug use. To accomplish this, we examined the correlation between IM use and 2 HRR-level variables from Dartmouth Atlas: total Part D spending per beneficiary (2010) and the proportion of 30-day prescriptions filled with brand-name products (2010).¹² A high correlation between these variables would suggest that high IM use may be

associated with the presence of key regional factors (eg, greater pharmaceutical marketing, influential prescribing thought leaders).

Covariates

We grouped covariates into 3 main categories: sociodemographics, health status, and care-seeking factors. Sociodemographics included beneficiary age, sex, race/ethnicity, and an indicator of low-income subsidy (LIS) and/or dual eligible status. In addition, beneficiary ZIP code of residence was used to classify beneficiaries' geographic location as rural versus urban.¹³ For health status, we included the beneficiary's average number of unique medications dispensed in each year (2009/2010), an indicator for end-stage renal disease, and 8 conditions known to inform antidiabetic treatment decisions. There were 6 conditions that were captured in the CCW (ie, diabetes, acute myocardial infarction, chronic kidney disease, heart failure, hypertension, and hyperlipidemia),¹⁴ and we created 2 dichotomous variables for peripheral vascular disease and pancreatitis/pancreatic cancer using inpatient, outpatient, and carrier files.^{15,16} In addition, we created a comorbidity risk score using the RxHCC.¹⁷ The RxHCC score considers age, sex, and documented comorbid diseases and is designed to predict future Part D spending for purposes of risk adjustment. Although there is slight overlap between the conditions included in the RxHCC score and our individual condition variables, we chose this conservative approach to modeling to remove as much variation in IM prescribing as possible caused by health status. To measure diabetes disease severity, we created a categorical variable for each of the following diabetes complications: diabetic neuropathy, diabetic nephropathy, diabetic retinopathy, and diabetes with peripheral vascular disease.¹⁸ These variables were created based on ICD-9 codes in inpatient, outpatient, and carrier files in 2009 or 2010. For care-seeking factors, we calculated the total number of unique prescribers of antidiabetic drugs for each beneficiary during the study period.

For descriptive purposes, we linked PDE records to the Prescriber Characteristics file to examine the primary specialty code of the prescriber associated with each prescription. To examine if regions where beneficiaries were more likely to be seen by an endocrinologist had higher rates of IM use, we created a beneficiary-level dichotomous variable indicating receipt of any antidiabetic prescription from an endocrinologist.^{19–21}

Statistical Analysis

We conducted analyses using Stata version 11.0 (Stata-Corp LP, College Station, TX). Descriptive statistics were examined for all variables, and *t* tests and χ^2 tests were used to assess differences in patients who did and did not use an IM during the study period. We calculated rates of HRR-level IM use via logistic regression at the beneficiary level with HRR indicators and adjusted for sociodemographics and health status. HRRs were ranked by the proportion of beneficiaries receiving an IM among those using any antidiabetic drug and then divided into quintiles. In addition, we calculated rates of HRR-level use of metformin, sulfonylureas, and TZDs and adjusted for sociodemographics and health status. To allow for a comparison in regional variation of antidiabetic drug use, we calculated coefficients of variation (standard deviation divided by the mean) for the adjusted (sociodemographics and health status) rates of antidiabetic drug use among these 3 subclasses as well as for IM use.

Descriptive statistics were examined for beneficiary and plan costs among those who did and did not use an IM, adjusting for sociodemographics and health status.

To examine whether regional variation was a result of differences in Part D plan formulary coverage of IMs, we conducted a sensitivity analysis that added an indicator variable for Part D plan to the multivariable regression. In addition, we conducted a sensitivity analysis that adjusted the rates of HRR-level IM not only for sociodemographics and health status, but also for receipt of any antidiabetic prescription from an endocrinologist. Finally, we examined antidiabetic prescribing by endocrinologist specialty by quintiles of IM use.

Results

Characteristics of the Study Sample

We identified 238 499 beneficiaries 65 years old enrolled in fee-for-service Medicare and Part D in 2009–2010 and who filled at least 1 prescription for an antidiabetic medication. In our sample, 29 933 (12.6%) filled at least 1 prescription for an IM, of which the DPP-4 inhibitors (sitagliptin and saxagliptin) were most commonly used ($n = 26\,939$ beneficiaries; 11.3%), followed by exenatide and liraglutide ($n = 3718$; 1.6%). For the entire sample, the most common non-IM antidiabetic medications used were: metformin (62.6% of beneficiaries), sulfonylureas (49.4%), insulins (31.6%), and TZDs (21.4%). Compared with those using a non-IM antidiabetic medication, beneficiaries using an IM were more likely to be Asian/Pacific Islander, have LIS/dual eligibility, live in an urban area, use more medications per year, have greater comorbidity (including diabetes complications), and have received an antidiabetic prescription from an endocrinologist (all P values <0.001 ; Table 1).

Regional Variation in IM Use

Nationally, HRRs had a median of 11.0% of beneficiaries filling a prescription for an IM among those filling any anti-diabetic prescription (Table 2). This (unadjusted) proportion ranged more than 3-fold between the 5th and 95th percentiles of 5.6% to 18.3%, respectively. After adjusting for sociodemographic and health status factors (including diabetes severity), this range was similar (5.2% to 17.0%; Table 2; Figure 1). HRRs with the lowest (adjusted) proportions of IM use were the following: Everett, WA (3.2%); Cedar Rapids, IA (3.4%); Marquette, MI (3.9%); Wausau, WI (4.2%); and Portland, OR (4.4%). HRRs with the highest (adjusted) proportions of IM use were the following: Manhattan, NY (27.1%); Panama City, FL (23.5%); Newark, NJ (23.2%); East Long Island, NY (21.5%); and Hackensack, NJ (21.3%).

Variation across HRRs was substantially higher for IMs than for other diabetes classes. After adjusting for sociodemographic and health status (including diabetes severity) factors, the proportion of beneficiaries filling a prescription for metformin, a sulfonylurea, or a TZD among those filling any antidiabetic prescription ranged between the 5th and 95th percentiles of 55.9% to 71.1%, 42.1% to 56.1%, and 14.3% to 27.1%, respectively (Table 3). The coefficient of variation for IM use (33.6) was 4.5 times higher than that for metformin (7.4), 3.8 times higher than that for sulfonylureas (8.8), and 1.7 times higher than that for TZDs (19.4). Compared with regions in the lowest quintile of IM use, beneficiaries in

regions in the highest quintile were also more likely to receive an antidiabetic prescription from an endocrinologist (11.8% vs 6.4%; data not shown).

In the 2 sensitivity analyses (ie, adding an indicator variable for Part D plan and adjusting for receipt of any antidiabetic prescription from an endocrinologist), we found nearly identical results to the main analysis (data not shown).

Cost

Among those beneficiaries using an antidiabetic drug, the average annual Part D plan costs for all antidiabetic drugs across the 2 years (after adjusting for demographics and health status) were 155% higher for IM users than non-IM users (\$1067 vs \$418). Similarly, out-of-pocket beneficiary costs were 144% higher for IM versus non-IM users (\$369 vs \$151). Furthermore, significant correlations were found between IM use (adjusted for sociodemographics and health status) and total Part D spending per beneficiary in 2010 ($r = 0.57$) and the proportion of 30-day prescription fills for brand-name products in 2010 ($r = 0.74$).

Discussion

For approximately 4 decades, researchers have reported regional variation in health care use.^{22–24} Our findings extend the field by focusing on variation in the use of a new drug class—the IMs—for a condition where many other established and lower-cost therapeutic options exist. We found more than 3-fold variation across regions in the proportion of beneficiaries filling an IM prescription, after adjusting for sociodemographics and health status, including diabetes severity. The variation in IM use was substantially greater than the variation detected for metformin, sulfonylurea, and TZD use. In addition, IM use was associated with substantially greater costs for both Part D plans and patients, highlighting the economic importance of regional variation in brand-name drug use.

The variation that we observed may reflect considerable uncertainty among providers regarding the risks and benefits of this class and is consistent with previous research showing that regional variation is more pronounced when decisions are discretionary.²² Uncertainty in IM prescribing may be ascribed to the lack of comparative effectiveness data available to answer the most important gap in the management of type 2 diabetes—that is, “Which drug should be added in patients not achieving target hemoglobin A1c levels from metformin alone?”²⁵ Our findings suggest that prescribing of IMs may be driven more by regional factors such as prescriber practice styles or local opinion leaders than by patient characteristics.²² In addition, regions with high IM use were also those with high overall brand-name drug use and with higher overall Part D spending. Taken together, these cost-related findings raise concerns about the impact of higher costs on Part D plan resource allocation and patient adherence. Furthermore, a common criticism of regional variation research is the lack of accounting for differences in case mix (ie, patient health status) across regions. We found that adjusting regional estimates of IM use for several disease severity indicators did nothing to attenuate the 3-fold variation in prescribing.

Current guidelines for older adults with diabetes suggest that after the use of metformin, glucose-lowering medication therapy should be individualized, but the guidelines do not give specific drug recommendations.¹ Thus, uncertainty remains regarding the relative safety and effectiveness of IMs and their place in the diabetes treatment regimen. IM use is considered potentially advantageous as second-line therapy in patients who have exhausted first-line therapy (metformin), who are at high risk of hypoglycemia, and/or in whom weight gain would be detrimental.⁴ It is doubtful, however, that variation in these risks or other clinical characteristics not captured by our case-mix variables explains why more than 1 in 4 Medicare beneficiaries filling antidiabetic prescriptions in Manhattan, NY, received an IM, compared with less than 1 in 20 in Everett, WA.

Regional variation in prescription drug use may lead to excess out-of-pocket costs for some beneficiaries. In fact, we found that IM users faced 155% higher Part D plan and 144% higher patient costs for antidiabetic prescriptions compared with non-IM users. Prescription drug costs are particularly concerning for older adults, who face a high financial burden from medications and are often burdened with cost-related medication nonadherence.²⁶

One cause of regional variation in prescription drug use may be idiosyncratic provider practice patterns. In fact, we found that beneficiaries living in regions in the highest quintile of IM use were almost 2 times more likely to receive an antidiabetic prescription from an endocrinologist compared with regions in the lowest quintile. Although this finding may reflect disease severity that we were unable to measure (such that specialists are more likely to care for sicker patients), we know from prior research that specialists are faster than generalists to adopt new medical technologies.²⁷ Rapid adoption is appropriate if the new drug is for patients likely to benefit, but it would be potentially inappropriate for use in patients who would receive no added clinical benefit while incurring added cost and being placed at increased risk.^{27–29} Moreover, an antidiabetic drug for an older adult should be chosen with drug safety as a top priority.^{5–7}

Our study has important limitations. We adjusted our measures for sociodemographic and health status factors but not for Part D plan characteristics (eg, prior authorization, tiered copayments, step-therapy protocols), which may affect medication use. Despite this, we conducted a sensitivity analysis with an indicator variable for Part D plan included in the multivariable regression, and the results were nearly unchanged. In addition, although we accounted for several important sociodemographic and health status factors that may have affected the outcome, there may have been unmeasured differences across HRRs for which it was not possible to control (eg, patient preferences, body mass index). However, given that the RxHCC classification system outperforms most risk adjustment models³⁰ and that we also controlled for important conditions for which prescribing of antidiabetics may inform treatment decisions, we expect bias to be minimal. We also did not have information on the intensity of pharmaceutical marketing, which could vary by region and affect new drug use. Future research is needed to elucidate the reasons for differences in new drug use across regions. Finally, we did not measure clinical outcomes and are ultimately unable to determine which level of IM use is clinically appropriate.

Conclusion

In conclusion, among Part D beneficiaries using antidiabetic drugs, substantial geographic variation exists in the use of IMs that is not accounted for by sociodemographic and health status factors. This variation is substantially greater than the variation observed among older diabetes drugs. These geographic differences subject some older adults, more than others, to the potential benefits, risks, and costs of this new class of diabetes medications. More robust comparative effectiveness data are needed to clarify where IMs fit over other second-line agents in the treatment of diabetes in older adults.

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Appendix

Diabetes Medications

Biguanides

Metformin
 Sulfonylureas
 Glimepiride
 Glyburide
 Glipizide
 Chlorpropamide
 Acetohexamide
 Tolbutamide
 Tolazamide
 Meglitinides
 Repaglinide
 Nateglinide
 Thiazolidinediones
 Pioglitazone
 Rosiglitazone
 α -Glucosidase inhibitors
 Acarbose
 Miglitol
 DPP-4 inhibitors
 Sitagliptin
 Saxagliptin
 Glucagon-like peptide-1 receptor agonists
 Exenatide
 Liraglutide
 Insulins
 Insulin aspart
 Insulin regular
 Insulin lispro
 Insulin glargine
 Insulin detemir
 Insulin NPH
 Insulin glulisine
 Amylin mimetics
 Pramlintide

Figure 1.

Proportion of beneficiaries receiving an incretin mimetic among those receiving any antidiabetic medication, by hospital referral region.^a

^aAdjusted for sociodemographic factors (age, gender, race, low-income subsidy/dual eligible status, and urban) and health status factors (end-stage renal disease; indicators for acute myocardial infarction, chronic kidney disease, heart failure, hyperlipidemia, hypertension, peripheral vascular disease, and pancreatitis; RxHCC score; and diabetes complications).

Table 1

Individual-Level Characteristics of Antidiabetic Medication Users 65 Years Old in Medicare Part D, 2009–2010.

Variable	Overall	No Incretin Mimetic Use ^a	Incretin Mimetic Use	P Value
	n = 238 499	n = 208 566	n = 29 933	
Sociodemographic	—	—	—	
Age, mean (SD)	75.0 (6.9)	75.1 (7.0)	74.3 (6.6)	<0.001
Women	146 971 (61.6)	128 734 (61.7)	18 237 (60.9)	0.008
Race/Ethnicity	—	—	—	<0.001
White	167 181 (70.1)	146 496 (70.2)	20 685 (69.1)	—
Black	28 344 (11.9)	25 586 (12.3)	2758 (9.2)	—
Asian/PI	12 156 (5.1)	9929 (4.8)	2227 (7.4)	—
Hispanic	26 910 (11.3)	23 144 (11.1)	3766 (12.6)	—
Other	3908 (1.6)	3411 (1.6)	497 (1.7)	—
LIS/Dual eligible	113 193 (47.5)	98 280 (47.1)	14 913 (49.8)	<0.001
Urban	175 000 (73.4)	151 452 (72.6)	23 548 (78.7)	<0.001
Health status	—	—	—	—
Medicare status	—	—	—	<0.001
Without ESRD	235 390 (98.7)	205 635 (98.6)	29 755 (99.4)	—
With ESRD	3109 (1.3)	2931 (1.4)	178 (0.6)	—
Number of medications per year, mean (SD)	8.6 (4.5)	8.4 (4.4)	10.1 (5.0)	<0.001
RxHCC score ^b	1.28 (0.4)	1.28 (0.4)	1.33 (0.4)	<0.001
Diabetes	235 290 (98.7)	205 477 (98.5)	29 813 (99.6)	<0.001
Acute myocardial infarction	18 269 (7.7)	16 073 (7.7)	2196 (7.3)	0.024
Chronic kidney disease	87 682 (36.8)	75 270 (36.1)	12 412 (41.5)	<0.001
Heart failure	104 737 (43.9)	90 690 (43.5)	14 047 (46.9)	<0.001
Hypertension	230 066 (96.5)	200 920 (96.3)	29 146 (97.4)	<0.001
Hyperlipidemia	220 034 (92.3)	191 434 (91.8)	28 600 (95.6)	<0.001
Peripheral vascular disease	59 856 (25.1)	51 637 (24.8)	8219 (27.5)	<0.001
Pancreatitis/pancreatic cancer	4294 (1.8)	3650 (1.8)	644 (2.2)	<0.001
Diabetes complications ^c	—	—	—	<0.001
0	117 647 (49.3)	105 305 (50.5)	12 342 (41.2)	—
1–2	106 257 (44.6)	91 121 (43.7)	15 136 (50.6)	—
3–4	14 595 (6.1)	12 140 (5.8)	2455 (8.2)	—
Care seeking	—	—	—	—
Prescription (antidiabetic) from an endocrinologist	19 216 (8.1)	14 229 (6.8)	4987 (16.7)	<0.001
Number of antidiabetic prescribers, mean (SD)	1.7 (1.1)	1.7 (1.0)	2.0 (1.3)	<0.001

Abbreviations: PI, Pacific Islander; ESRD, end-stage renal disease; LIS, low-income subsidy.

^aUse of any antidiabetic medication other than an incretin mimetic.

^bThe RxHCC score considers age, sex, and documented comorbid diseases and is designed to predict future Part D costs for purposes of risk adjustment.

^cDiabetes complications: categorical variable representing the following 4 complications: diabetic neuropathy, diabetic nephropathy, diabetic retinopathy, and diabetes with peripheral vascular disease.

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Table 2

HRR-Level Percentage of Beneficiaries Using an Incretin Mimetic.

Variable	Unadjusted	Adjusted for Sociodemographic Factors ^a	Adjusted for Sociodemographic and Health Status Factors ^b
Mean HRR	11.3%	11.1%	11.0%
Median HRR	11.0%	10.8%	10.8%
Minimum	3.6%	3.3%	3.2%
5th Percentile of HRRs	5.6%	5.5%	5.2%
95th Percentile of HRRs	18.3%	18.0%	17.0%
Maximum	28.0%	28.3%	27.1%

Abbreviation: HRR, hospital referral region.

^aSociodemographic factors included age, gender, race, low-income subsidy/dual eligible status, urban.^bHealth status factors included end-stage renal disease; indicators for acute myocardial infarction, chronic kidney disease, heart failure, hyperlipidemia, hypertension, peripheral vascular disease, and pancreatitis; RxHCC score; and diabetes complications.

Table 3HRR-Level Percentage of Beneficiaries Using Metformin, Sulfonylureas, and Thiazolidinediones.^a

Variable	Metformin	Sulfonylureas	Thiazolidinediones
Mean HRR	63.1%	49.2%	20.3%
Median HRR	63.1%	49.3%	20.0%
Minimum	53.4%	37.8%	12.3%
5th Percentile of HRRs	55.9%	42.1%	14.3%
95th Percentile of HRRs	71.1%	56.1%	27.1%
Maximum	75.0%	58.9%	31.4%
Coefficient of variation ^b	7.4	8.8	19.4

^a Adjusted for sociodemographic (age, gender, race, low-income subsidy/dual eligible status, and urban) and health status factors (end-stage renal disease; indicators for acute myocardial infarction, chronic kidney disease, heart failure, hyperlipidemia, hypertension, peripheral vascular disease, and pancreatitis; RxHCC score; and diabetes complications).

^b Coefficient of variation is calculated as the standard deviation divided by the mean.