NOTE:

These materials were prepared by subcontractors for consideration by the *Committee on Geographic Variation in Health Care Spending and Promotion of High-value Care*. These analyses were commissioned and overseen by the Committee. However, the findings and views expressed in the subcontractor reports do not necessarily reflect those of the NRC/IOM or the Committee. Neither the methodology nor the subcontractor reports have been subject to formal institutional review for the Interim Report. As the committee continues to review the findings from the analyses contained herein, we invite you to provide feedback on the content of these reports. Please note that any comments will be entered into the project's public access file, and will be available for public review.

Provide Feedback

Geographic Variation in Health Care Spending and Promotion of High-Value Health Care Medicare Part D

Final Report

Prepared for:

The Institute of Medicine Committee on Geographic Variation in Health Care Spending and Promotion of High-Value Health Care

Submitted by: **University of Pittsburgh**

May 25, 2012

Principal Investigator:

Yuting Zhang, PhD

Assistant Professor of Health Economics Director,
Pharmaceutical Economics Research Group
University of Pittsburgh
(412) 383-5340
ytzhang@pitt.edu

Statisticians/Analysts:

Seo Hyon Baik, PhD Shang-Hua (Sean) Wu, MS

Pharmaceutical Economics Research Group
University of Pittsburgh

Acknowledgements

Our team benefited from the individuals who generously offered their time and knowledge. Our special thanks to the following: Katherine Baicker, A. Mark Fendrick, and Cameron M. Kaplan.

TABLE OF CONTENTS

TABLE OF FIGURES

REPORT 1: Regional Analysis Masks Substantial Local Geographic Variation

ABSTRACT

Background

Wide geographic variation in healthcare spending has generated concern about inefficiency and policy debate about geographic-based payment reform. Evidence of variation has focused on hospital referral regions (HRRs), which incorporate numerous local hospital service areas (HSAs). If there is substantial variation across local areas within HRRs, then policies focusing on HRRs may be poorly targeting.

Methods

Using pharmacy and medical claims data from a 5% random sample of Medicare beneficiaries in 2006-2009, we compared variation in utilization in 306 HRRs and 3436 HSAs. We adjusted for beneficiary-level demographics, insurance status, and clinical characteristics to calculate adjusted use and spending.

Results

There is substantial local variation in drug and non-drug utilization and spending. There is little evidence of substitution of one component of healthcare for another at either the HSA or HRR levels. However, substantial dispersion of local spending exists within HRRs, with many low-spending HSAs located within the borders of high-spending HRRs and vice versa. Only about half of the HSAs located within the borders of the highest spending quintile of HRRs are in the highest spending quintile of HSAs; conversely, only about half of the highest spending HSAs are located within the borders of the highest-spending HRRs.

Conclusions

The effectiveness of payment reforms in reducing overutilization while maintaining access

to high quality care depends crucially on the effectiveness of targeting. Our analysis suggests that HRR-based policies may be too crude to promote the best use of healthcare resources.

INTRODUCTION

A substantial body of evidence has emerged highlighting wide geographic variation in healthcare spending that is not driven by patient characteristics and not associated with the quality of care or patient outcomes.[1-7] In light of this evidence, many policy proposals suggest targeting high spending areas for lower Medicare payments or other coverage constraints, focusing on areas such as Dartmouth hospital-referral regions (HRRs). The effectiveness of these policies in reducing overutilization while maintaining access to high quality care depends crucially on the effectiveness of targeting: if there is substantial variation across local areas within HRRs, then focusing on high-cost HRRs may leave many high-spending locales untouched while inadvertently penalizing some low-spending locales. Furthermore, focusing on one type of spending in isolation may be misleading if different areas substitute one kind of care for another.

We compare variations in medical spending and prescribing patterns at the broader market level, the 306 Dartmouth HRRs, to variation within those markets, the 3436 Dartmouth hospital-service areas (HSAs).[1] While HRRs represent the areas served by large tertiary hospitals where patients were referred for major cardiovascular surgical procedures and for neurosurgery and abstract from local population differences, HSAs better capture the local health care markets where Medicare beneficiaries received most of their care. Specifically, we examine: (1) variation in prescription drug and medical care spending and use across HSAs versus across HRRs; (2) the association between variation in different types of services across HSAs versus across HRRs; and (3) the degree to which high-spending HSAs are clustered together within high-spending HRRs. This facilitates evaluation of the effectiveness of targeting at different levels of geographic variation and the implications of targeting based on payments bundles across

different silos of spending.

METHODS

Data source and study sample

We obtained 2006-2009 enrollment, drug event and medical claims data from the Centers for Medicare & Medicaid Services (CMS) for a 5% random sample of Medicare beneficiaries. For each year between 2007 and 2009, we identified all beneficiaries having at least one month enrollment in stand-alone Part D (PDP) plans because CMS only has both medical and drug data for those enrolled in PDP plans. Thus, beneficiaries in our sample either had full-year or partial-year enrollment in Parts A, B, and D. We used two methods to account for partial-year enrollment described below. The resulting sample consisted of 1,013,477 beneficiaries in 2007, 1,024,183 in 2008, and 1,022,662 in 2009; 915,788 were in both 2007 and 2008 and 821,990 were in all three years, and in total we had 3,060,322 beneficiary-year observations when pooling three years together. We assigned each beneficiary to 1 of 306 HRRs or 3436 HSAs based on the beneficiary's ZIP Code of residence.[1] HSAs are nested within HRRs. The study was approved by the Institutional Review Board at the University of Pittsburgh.

We conducted sensitivity analysis for two subpopulations: (1) those aged ≥65 and (2) those enrolled for the full year or until they died, to ensure that our results are not substantially affected by a small proportion of disabled beneficiaries or those switching plans within the year (see Appendix Table 1). The results for these subpopulations are quite similar to the main results presented here.

Outcomes

Our outcomes were utilization of and spending on medical services and prescription drugs. All outcome measures were calculated in per-person-per-year units (with spending of part-year enrollees annualized). For medication use, we defined two outcomes: (1) total gross drug spending including Part D plan payment before rebates, beneficiary out-of-pocket spending, and subsidy amount; and (2) number of monthly prescription drugs (=1 if days supply ≤30; =days supply/30 if days supply >30). For the medical services, we defined four outcomes: (1) total non- drug medical spending, (2) number of inpatient admissions; (3) number of outpatient office visits; and (4) number of emergency room (ER) visits. Total non-drug medical spending included Medicare and beneficiary payment for all medical services (including inpatient, outpatient, physician, home health, hospice, skilled nursing home, and medical devices) and was adjusted for local price-level differences using county-level factor prices given to us by the Medicare Payment Advisory Commission (MedPAC).[7,8] We did not adjust drug spending for regional price differences because the variation in drug prices among regions was negligible.[4]

Adjustment variables

To account for the difference in population mix across regions, we adjusted for three major categories of beneficiary-level variables: patient demographics, insurance status, and clinical characteristics. Demographics include age in 5-year increments (<=34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80-84, 85-89, 90-94, 95+), gender (1=female; 0=male), race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, Asian, and other). Part D data have an enhanced Research Triangle Institute Race Code verified by first and last name algorithms, with much improved sensitivity (>77%) and Kappa coefficient (0.79).[9]

We adjusted for insurance status and a proxy for income. We used variables indicating Medicaid coverage (available to those under about 75% of the Federal poverty level (FPL), but

with some state variation) and non-dual federal low-income subsidies (which vary based on FPL cut-points) to create income bins: <75% FPL, 75%-135% FPL, 135-150% FPL, and >150% FPL. We also included two indicators for supplementary drug coverage using Part D data: those with generic-coverage in the "donut hole" gap and those with both generic and brand-name drug in the gap. We also controlled for share of the year the beneficiary was enrolled. In addition, we adjusted for an indicator of being disabled (<65 years old) for beneficiaries who were eligible for Medicare because of disability.

Clinical characteristics included risk scores and indicators for institutionalization (defined as having 90 days in a nursing home) and death during the year. We calculated the two prospective risk scores using prior-year diagnosis and spending: CMS Hierarchical Condition Category scores (CMS-HCC) for non-drug medical care services and the analogous prescription drug hierarchical condition category (RxHCC) scores.[10] We used prior-year instead of current-year diagnosis and spending to calculate risk score (except for the 4% of the sample who are new enrollees, for whom we use concurrent risk scores based on age and gender). This will mitigate – but not eliminate – the potential endogeneity of physician's coding; for example, physicians in higher-spending regions may code patients as sicker than physicians in lower-spending regions code similar patients. However, results shown below are robust to exclusion of risk scores.

Statistical analysis

We used these data to generate an adjusted average value for each outcome for each HSA (or HRR). We pooled three years (2007-2009) and conducted an individual-level linear regression for each outcome.[11] Each regression included HSA (or HRR) indicator variables, year indicators (2007, 2008), all of the adjustment variables described above. In addition, all the regressions were weighted by the percent of year enrolled so those who only had partial-year

enrollment would contribute less to the model. We then calculated the predicted value for each HSA (or HRR) using the estimating equation evaluated at national averages for the covariates, thus capturing variation at the HSA (or HRR) level that was purged of variation in population characteristics across HSAs (or HRRs).

We use these adjusted HSA (or HRR) outcomes to perform three sets of analysis. First we described the degree of variation between HSAs (or HRRs), calculating statistics such as ratios of 90^{th} to 10^{th} percentiles and 75^{th} to 25^{th} percentiles and coefficients of variation (COV). We included only HSAs with 50 enrollees or more to avoid the introduction of noise driven by small cell sizes and used the same sample to conduct HRR level analysis.

Second, we explored the relationships between spending on different types of care – such as pharmaceutical, inpatient, and outpatient – at the HSA (or HRR) level. We calculated Pearson correlation coefficients between adjusted outcomes. (Spearman correlation results were quite similar.) This sheds light on the degree to which local area providers substitute one type of care for another.

Finally, we evaluated the degree to which HSAs with similar spending levels cluster together within HRRs. Clearly there will be a correlation between spending at the HSA level and spending at the HRR level – HRRs are just an aggregation of HSAs – but we assessed the degree of dispersion of HSA spending within HRRs. We evaluated the variation across HSAs within and between HRRs. We also divided HRRs into quintiles based on their adjusted pharmacy and non-pharmacy medical spending, and similarly divided HSAs into quintiles according to their adjusted spending. We then tabulated the share of high and low spending HSAs located within the borders of high and low spending HRRs.

RESULTS

Regional variations in adjusted outcomes

TABLES AND FIGURES

Table 1 presents the variation in pharmacy and non-drug medical spending, counts of monthly prescriptions filled, inpatient admissions, outpatient office visits and ER visits per person per year in different regions. Panel A shows the variation in spending at the HSA level. Beneficiaries in the median HSA filled 53 monthly prescription drugs per year, or 4.4 prescriptions per month, corresponding to $2912 in annual gross drug spending. Medical spending and drug spending are comparably variable, with coefficients of variation of .15. The ratio of drug spending at the 75th percentile to that at the 25th percentile is 1.21, whereas the corresponding ratio for drug counts is only 1.12. This suggests that variation in the mix of drugs prescribed is larger than variation in number of drugs prescribed. Of course, part of this variation may be due to other unmeasured patient characteristics or illness severity.

Panel B reports the analogous variation across HRRs. The pattern of variation across categories is quite similar, although the overall degree of variation is somewhat lower. We explore below whether high-spending HSAs are located primarily within high spending HRRs, or whether there is substantial variation between HSAs within HRRs.

Correlations across adjusted outcomes at the regional level

We next describe the association between local spending on different types of care.

Table 2 presents Pearson correlation coefficients for all the adjusted outcomes at the HSA and HRR level. There is a small positive correlation between drug spending and non-drug medical spending in HSAs ($r=0.16$, $p<0.05$). There is a stronger correlation between drug spending and outpatient visits than between drug counts and outpatient visits, although this

relationship is reversed for inpatient admissions and ER counts. There is very little correlation between outpatient visits and inpatient admissions. Thus, consistent with previous research at the HRR level, there appears to be little evidence of substitution between drug-intensive care and non-drug medical care at the local area-level.[4,12]

Variations across HSAs within HRRs

We last gauge the degree to which HSAs with high spending are concentrated together in HRRs with high spending. A formal test of whether there is variation across HSAs nested within HRRs can (unsurprisingly) reject the null hypothesis of no systematic HSA variation within HRRs (joint $F=4.86$, $p<0.01$). About 59% of the variation in adjusted HSA drug spending is within HRRs, while 41% is between. For example, Manhattan is one of the HRRs with the highest adjusted drug spending and Albuquerque is one of the lowest – but there is substantial dispersion in spending across the HSAs within those HRRs: the lowest-spending HSA in Manhattan has lower spending than about 25% of the HSAs within Albuquerque.

Table 3 shows a cross-tab of HSA spending quintiles and HRR spending quintiles, with Panel A based on adjusted drug spending and Panel B based on adjusted non-drug medical spending. Each cell represents the number of HSAs falling into that row and column. The columns are defined based on dividing HSAs into spending quintiles. The first column of Panel A, for example, is HSAs with less than $2564 annual adjusted drug spending. Thus there are by definition 20% of HSAs in each column. The rows are defined based on dividing HRRs into quintiles of HRR spending and then looking at the HSAs within those HRRs. The first row of Panel A, for example, is HSAs located within HRRs where the average adjusted annual drug spending is less than $2768 (threshold of 1st quintile of HRR drug spending). Thus there may be more or fewer than 20% of HSAs represented in each row. The more geographically clustered

together HSAs are based on their spending level, the more they should be located in the diagonal cells.

Table 3 suggests that there is substantial dispersion of HSAs, with many low-spending HSAs located within the borders of high-spending HRRs and many high-spending HSAs located within the borders of low-spending HRRs. For example, only 55% of the HSAs located within the highest drug-spending quintile of HRRs are in fact in the highest drug-spending quintile of HSAs. Similarly, only 54% of the highest spending HSAs are located within the borders of the highest-spending HRRs. There is slightly less dispersion in non-prescription medical spending, but the pattern is quite similar overall. The Figure 1 illustrates these results in maps: while many high-spending HSAs are within the borders of high-spending HRRs and low-spending HSAs are within the borders of low-spending HRRs, many are not.

DISCUSSION

Much policy attention has been drawn to the large and persistent geographic variation in healthcare spending – for good reason. The presence of such variation (in the absence of commensurate variation in patient needs or even in health outcomes) suggests that high-intensity practice patterns in some areas signal inefficient resource use. This has led to discussion of policy levers to rein in spending in high-utilization, high-cost areas, such as lowering Medicare payments to providers in those areas.

Analysis has primarily been focused on variation between HRRS – areas defined based on large tertiary facilities and incorporating numerous HSAs. There are advantages to looking at such large areas (they may be large enough to capture more homogeneous patient pools), but the disadvantage of such an exclusive focus is that it can mask substantial heterogeneity at the more

local level. This is particularly important when considering the effects of policy levers that aim to act on local practice patterns for primary care, for example.

We examined the degree of heterogeneity within HRRs. We found that (1) there is substantial local variation in utilization and spending for both drug and non-drug medical spending; (2) there is little evidence of substitution of one kind of care for another at the local level, parallel to similar findings at the HRR level; (3) there is substantial dispersion of local spending within HRRs.

These findings are of course subject to several limitations. First, our analysis is based on the Medicare population. Patterns among the commercially insured may differ. Medicare does, however account for 20% of all national health care spending as of 2010,[13] and many of the policy levers discussed apply to Medicare payment rates. Second, our risk-adjusters are imperfect and we do not capture patient preferences. To the extent that these vary across localities, they could drive some of the observed patterns of heterogeneity. It is somewhat reassuring on this front that patterns of unadjusted outcomes are quite similar to those with adjusted outcomes. Third, causal connections are inherently difficult to draw from ecological data. While the variation described here (and elsewhere in the literature) is strongly suggestive of inefficient use of resources, it is difficult to use these data to forecast what the effect of different policy levers might be on spending patterns.

Nevertheless these findings do have policy implications. Policies that aim to reduce the spending in high-cost areas by targeting high-spending HRRs may fail on both sensitivity and specificity: a substantial number of high-spending HSAs are in low-spending HRRs, and a substantial number of the HSAs in high-spending HRRs are low-spending HSAs.

This does not, however, tell us what the "right" level of aggregation for policy is. There is clearly variation in spending within HSAs – should policy focus on an even more local level? The movement towards Accountable Care Organizations (ACOs) aims to tie payments to the care delivered by provider groups that are large enough to pool risk and abstract from individual-level variation in needs and idiosyncratic outcomes, but small enough to hold the group accountable for the use of resources. In the absence of formal ACOs, payments tied to local area practice patterns aim to accomplish similar goals. This analysis suggests that policies focused exclusively on the hospital referral region may be too blunt to promote the best use of health care resources.

TABLES AND FIGURES

Table 1 Variation in Adjusted Medicare Drug and Non-Drug Medical Spending, Counts of Monthly Prescriptions Filled, Inpatient Admissions, Outpatient Office Visits, and Emergency Room Visits, All in Per-Person-Per-Year Units in Different Regions (among Hospital-Service Areas with Greater Than 50 Beneficiaries)

Panel A. Hospital-Service Areas (2913 out of 3436 HSAs)

	Min	10^{th}	25^{th}	Median	75^{th}	90^{th}	Max	Mean	S.D.	$75^{th}/25^{th}$	COV
Drug spending	888	2405	2630	2912	3188	3441	5232	2922	431	1.21	0.15
Drug counts	27.9	46.9	49.6	52.7	55.7	58.9	75.1	52.8	4.89	1.12	0.09
Medical spending	6815	9869	10761	11789	12916	14162	24306	11951	1803	1.20	0.15
IP counts	0.16	0.35	0.39	0.44	0.50	0.56	0.90	0.45	0.09	1.28	0.20
OP counts	1.95	5.19	5.92	6.55	7.24	7.95	12.89	6.58	1.16	1.22	0.18
ER counts	0.09	0.56	0.63	0.72	0.81	0.92	2.40	0.73	0.16	1.27	0.22
Total spending	9164	12641	13604	14720	15941	17224	28284	14873	1921	1.17	0.13

Panel B. Hospital Referral Regions (306 out of 306 HRRs)

	Min	10th	25th	Median	75th	90th	Max	Mean	S.D.	75th/ 25th	COV
Drug spending	2377	2654	2796	2945	3126	3284	4240	2977	273	1.12	0.09
Drug counts	43.1	48.0	50.3	52.4	54.2	56.2	64.6	52.3	3.13	1.08	0.06
Medical spending	7932	10392	10994	11716	12573	13575	19526	11844	1397	1.14	0.12
IP counts	0.3	0.36	0.39	0.43	0.47	0.50	0.61	0.43	0.05	1.19	0.13
OP counts	3.75	5.62	6.08	6.60	7.08	7.75	10.75	6.65	0.90	1.16	0.14
ER Counts	0.37	0.61	0.66	0.71	0.76	0.81	1.03	0.71	0.08	1.16	0.12
Total spending	10443	13218	13791	14764	15601	16575	23766	14821	1499	1.13	0.10

Abbreviations: IP = inpatient, OP = outpatient, ER = emergency room.

Table 2. Pearson Correlation Across Adjusted Medicare Pharmacy and Medical Spending and Counts in Per-Person-Per-Year Units in Different Regions (excluding Hospital-Service Areas with Fewer Than 50 Beneficiaries)

Panel A. Hospital-Service Areas (2913 out of 3436 HSAs)

Variable	Drug Counts	Non-drug Medical Spending	Inpatient Admissions	Outpatient/ Office visits	ER Counts
Drug Spending	**0.44**	**0.16**	0.02	**0.28**	**-0.04**
Drug Counts	**1.00**	**0.13**	**0.18**	**0.05**	**0.24**
Non-drug Medical Spending		**1.00**	**0.61**	**0.23**	**0.17**
Inpatient Admissions			**1.00**	**0.08**	**0.35**
Outpatient/Office visits				**1.00**	**-0.11**

Panel B. Hospital-Referral Regions (306 out of 306 HRRs)

Variable	Drug Counts	Non-drug Medical Spending	Inpatient Admissions	Outpatient/ Office visits	ER Counts
Drug Spending	**0.30**	**0.29**	0.07	**0.45**	**-0.25**
Drug Counts	**1.00**	**0.14**	**0.24**	-0.09	**0.35**
Non-drug Medical Spending		**1.00**	**0.62**	**0.47**	-0.07
Inpatient Admissions			**1.00**	0.08	**0.27**
Outpatient/Office visits				**1.00**	**-0.35**

Note: Correlations in **bold** indicates statistically significant at p-value <0.05.

Abbreviation: ER = emergency room.

Table 3. Quintile Analysis for Adjusted Pharmacy Spending and Non-drug Medical Spending Between Hospital-referral Regions and Hospital-service Areas

Panel A. Adjusted Pharmacy Spending

			Quintiles of Adjusted HSA Drug Spending					
	HSA Frequency Cell % Row % Column %		1 [$888, $2564]	2 ($2564, $2805]	3 ($2805, $3009]	4 ($3009, $3255]	5 ($3255, $5232]	Total
Quintiles of Adjusted HRR Drug Spending	1	[$2377, $2768]	272 9.3 47.5 46.7	171 5.9 29.8 29.3	72 2.5 12.6 12.4	41 1.4 7.2 7.0	17 0.6 3.0 2.9	573 19.7
	2	($2768, $2880]	133 4.6 25.5 22.9	155 5.3 29.7 26.6	133 4.6 25.5 22.8	81 2.8 15.5 13.9	20 0.7 3.8 3.4	522 17.9
	3	($2880, $3024]	97 3.3 16.4 16.7	130 4.5 21.9 22.3	169 5.8 28.5 29.0	129 4.4 21.8 22.1	68 2.3 11.5 11.7	593 20.4
	4	($3024, $3182]	63 2.2 9.6 10.8	91 3.1 13.9 15.6	141 4.8 21.6 24.2	198 6.8 30.3 34.0	161 5.5 24.6 27.7	654 22.5
	5	($3182, $4240]	17 0.6 3.0 2.9	36 1.2 6.3 6.2	68 2.3 11.9 11.7	134 4.6 23.5 23.0	316 10.9 55.3 54.3	571 19.6
		Total	582 20.0	583 20.0	583 20.0	583 20.0	582 20.0	2913 100

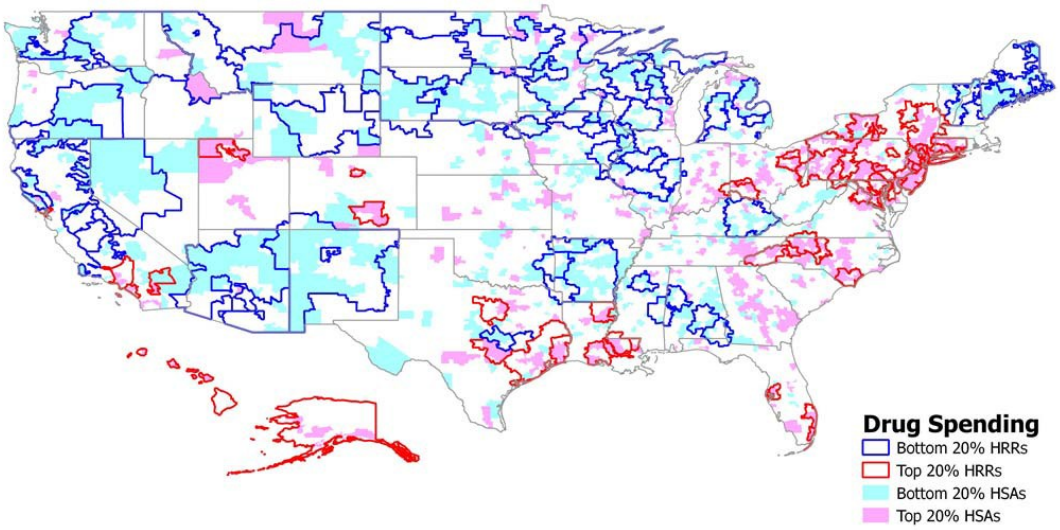
Panel B. Adjusted Non-drug Medical Spending

			Quintiles of Adjusted HSA Medical Spending					
	HSA Frequency Cell % Row % Column %		1 [$6815, $10515]	2 ($10515, $11404]	3 ($11404, $12198]	4 ($12198, $13244]	5 ($13244, $24306]	Total
Quintiles of Adjusted HRR Medical Spending	1	[$7932, $10738]	302 10.4 56.7 51.9	136 4.7 25.5 23.3	59 2.0 11.1 10.1	25 0.9 4.7 4.3	11 0.4 2.1 1.9	533 18.3
	2	($10738, $11393]	143 4.9 26.6 24.6	187 6.4 34.8 32.1	129 4.4 24.0 22.1	56 1.9 10.4 9.6	22 0.8 4.1 3.8	537 18.4
	3	($11393, $12077]	88 3.0 13.6 15.1	154 5.3 23.8 26.4	177 6.1 27.4 30.4	160 5.5 24.7 27.4	68 2.3 10.5 11.7	647 22.2
	4	($12077, $12717]	42 1.4 6.2 7.2	86 3.0 12.7 14.8	164 5.6 24.1 28.1	223 7.7 32.8 38.3	165 5.7 24.3 28.4	680 23.3
	5	($12717, $19526]	7 0.2 1.4 1.2	20 0.7 3.9 3.4	54 1.9 10.5 9.3	119 4.1 23.1 20.4	316 10.9 61.2 54.3	516 17.7
	Total		582 20.0	583 20.0	583 20.0	583 20.0	582 20.0	2913 100

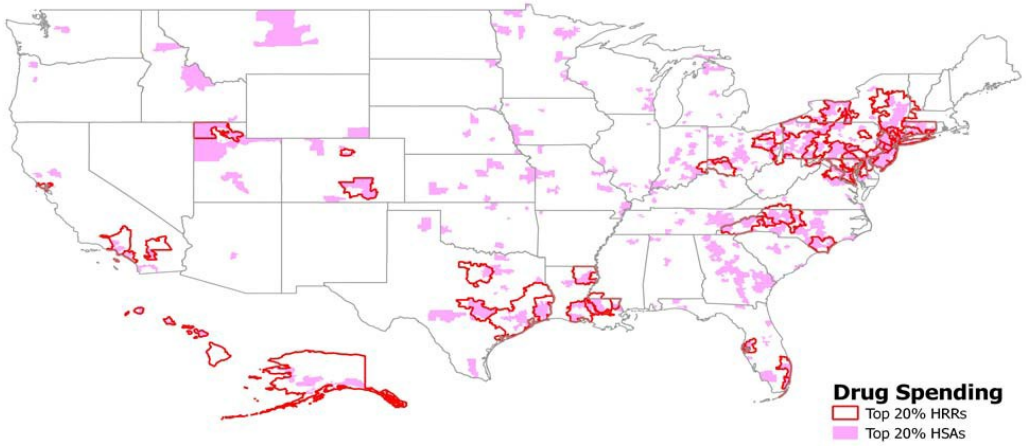
Note: Each cell represents the number of HSAs falling into that row and column. The columns are defined based on dividing HSAs based on quintiles of HSA spending (thus there are 20% of HSAs in each by definition). The rows are defined based on dividing HRRs based on quintiles of HRR spending (thus there may be > or < 20% of HSAs located within the borders of HRRs in each quintile of HRR spending).

Figure 1. Quintile Analysis for Adjusted Pharmacy Spending Between Hospital-referral Regions and Hospital-service Areas

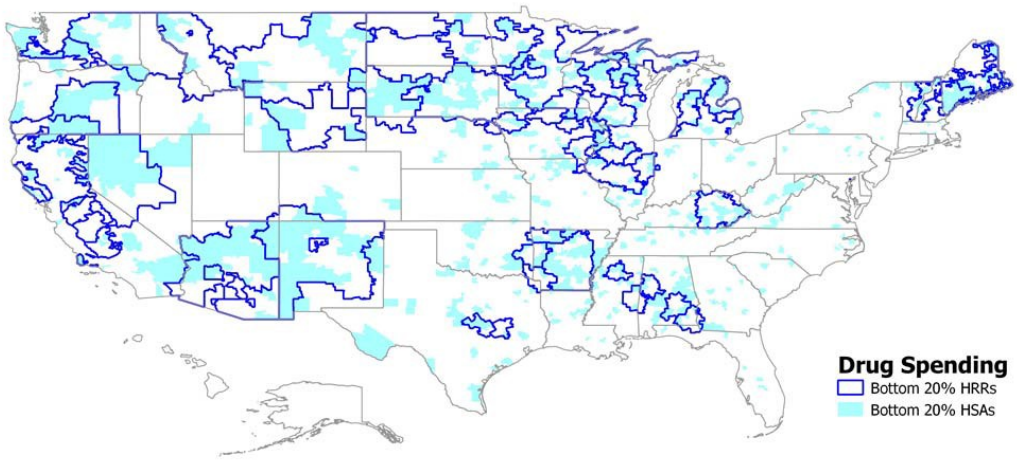
Panel A. Top 20% and bottom 20% HRRs and HSAs



Panel B. Top 20% HRRs and HSAs



Panel C. Bottom 20% HRRs and HSAs



APPENDIX

Appendix Table 1. Sensitivity Analysis for Variation in Adjusted Outcomes as in Table 1 in Different Hospital-Service Areas

Panel A. For those with full enrollment for the year or until death

	Min	10th	25th	Median	75th	90th	Max	Mean	S.D.	75th/ 25th	COV
Drug spending	768	2400	2640	2916	3192	3432	5352	2916	432	1.21	0.15
Drug counts	26	47	50	53	56	59	76	53	4.92	1.12	0.09
Medical spending	7800	11904	12864	13908	15096	16368	27336	14076	1860	1.17	0.13
IP counts	0.24	0.48	0.48	0.48	0.60	0.60	0.96	0.48	0.12	1.24	0.17
OP counts	2.04	5.28	6.00	6.72	7.32	8.04	13.32	6.72	1.2	1.23	0.18
ER Counts	0.12	0.60	0.72	0.84	0.84	0.96	2.4	0.84	0.12	1.25	0.20

Panel B. For those Aged >= 65

	Min	10th	25th	Median	75th	90th	Max	Mean	S.D.	75th/ 25th	COV
Drug spending	732	2136	2328	2580	2832	3048	5520	2592	384	1.21	0.15
Drug counts	30	48	51	54	57	60	77	54	4.92	1.12	0.09
Medical spending	7596	11472	12396	13560	14712	16140	25740	13704	1956	1.19	0.14
IP counts	0.24	0.36	0.48	0.48	0.60	0.60	1.08	0.48	0.12	1.25	0.18
OP counts	1.56	5.04	5.76	6.48	7.20	7.92	13.08	6.48	1.2	1.24	0.19
ER Counts	0.12	0.48	0.60	0.60	0.72	0.84	2.04	0.72	0.12	1.25	0.20

Abbreviations: IP = inpatient, OP = outpatient, ER = emergency room.
ean); ED = emergency department.

REFERENCES

1. The Dartmouth Atlas Project. The Dartmouth Atlas of Health Care. In. Lebanon, NH; 2010.
2. Fisher ES, Wennberg DE, Stukel TA, Gottlieb DJ, Lucas FL, Pinder EL. The implications of regional variations in Medicare spending. Part 2: health outcomes and satisfaction with care. Annals of Internal Medicine 2003;138:288-98.
3. Fisher ES, Wennberg DE, Stukel TA, Gottlieb DJ, Lucas FL, Pinder EL. The implications of regional variations in Medicare spending. Part 1: the content, quality, and accessibility of care. Annals of Internal Medicine 2003;138:273-87.
4. Zhang Y, Baicker K, Newhouse JP. Geographic variation in Medicare drug spending. New England Journal of Medicine 2010;363:405-9.
5. Zhang Y, Baicker K, Newhouse JP. Geographic variation in the quality of prescribing. New England Journal of Medicine 2010;363:1985-8.
6. Donohue JM, Morden NE, Gellad WF, et al. Sources of Regional Variation in Medicare Part D Drug Spending. New England Journal of Medicine 2012;366:530-8.
7. Report to the Congress: Regional Variation in Medicare Service Use. 2011. (Accessed November 18, 2011, at http://www.medpac.gov/documents/Jan11_RegionalVariation_report.pdf.)
8. Report to the Congress: Measuring Regional Variation in Service Use. 2009. (Accessed February 18, 2010, at http://www.medpac.gov/documents/Dec09_RegionalVariation_report.pdf.)
9. Creation of New Race-Ethnicity Codes and Socioeconomic Status (SES) Indicators for Medicare Beneficiaries. Final Report. Sub-Task 2. (Prepared by RTI International for the Centers for Medicare and Medicaid Services through an interagency agreement with the

Agency for Healthcare Research and Policy, under Contract No. 500-00-0024, Task No. 21). Agency for Healthcare Research and Quality, 2008. (Accessed March 16, 2010, at http://www.ahrq.gov/qual/medicareindicators/medicareindicators.pdf.)

10. 2011 RxHCC Model Software. 2011. (Accessed March 12, 2011, at http://www.cms.gov/MedicareAdvtgSpecRateStats/06_Risk_adjustment.asp#TopOfPage.)
11. Buntin MB, Zaslavsky AM. Too much ado about two-part models and transformation? Comparing methods of modeling Medicare expenditures. Journal of Health Economics 2004;23:525-42.
12. Zhang Y, Newhouse JP, Baicker K. Are Drugs Substitutes or Complements for Intensive (and Expensive) Medical Treatment. American Economic Review 2011;101:393-97.
13. Martin AB, Lassman D, Washington B, Catlin A, Team tNHEA. Growth In US Health Spending Remained Slow In 2010; Health Share Of Gross Domestic Product Was Unchanged From 2009. Health Affairs 2012;31:208-19.
14. Jonathan Skinner, Douglas Staiger, Fisher ES. Looking back, moving forward. NEJM 2010;362:5.
15. Song Y, Skinner J, Bynum J, Sutherland J, Wennberg JE, Fisher ES. Regional Variations in Diagnostic Practices. New England Journal of Medicine 2010:NEJMsa0910881.
16. Wennberg JE, Fisher ES, Skinner JS. Geography And The Debate Over Medicare Reform. Health Aff 2002:hlthaff.w2.96.
17. Gibson TB, Landrum MB, Batata A, Fendrick AM, Wang S, Chernew M. Regional variation in medication adherence. Forum for Health Economics & Policy 2011;14.
18. Neuman P, Strollo MK, Guterman S, et al. Medicare prescription drug benefit progress report: findings from a 2006 national survey of seniors. Health Aff (Millwood)

2007;26:w630-43.

19. American Heart Association. 2006 Heart and Stroke Statistical Update. Dallas, TX: American Heart Association; 2006.
20. Wu J-R, Moser DK, Chung ML, Lennie TA. Objectively Measured, but Not Self-Reported, Medication Adherence Independently Predicts Event-Free Survival in Patients With Heart Failure. Journal of Cardiac Failure 2008;14:203-10.
21. Wald NJ, Law MR. A strategy to reduce cardiovascular disease by more than 80%. BMJ 2003;326:1419.
22. Jessup M, Abraham WT, Casey DE, et al. 2009 focused update: ACCF/AHA Guidelines for the Diagnosis and Management of Heart Failure in Adults: a report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines: developed in collaboration with the International Society for Heart and Lung Transplantation. Circulation 2009;119:1977-2016.
23. Zhang Y, Lave JR, Donohue JM, Fischer MA, Chernew ME, Newhouse JP. The impact of Medicare Part D on medication adherence among older adults enrolled in Medicare-Advantage products. Medical Care 2010;48:409-17.
24. Choudhry NK, Avorn J, Glynn RJ, et al. Full coverage for preventive medications after myocardial infarction. N Engl J Med 2011;365:2088-97.
25. Zhang Y, Baicker K, Newhouse JP. Geographic variation in Medicare drug spending. N Engl J Med 2010;363:405-9.
26. Lee TH. Eulogy for a Quality Measure. N Engl J Med 2007;357:1175-7.
27. National Committee for Quality Assurance. State of Health Care Quality. In. Washington DC; 2010.