

Potential Cost Savings From Reduction of Regional Variation in Medicare Spending: A Statistical Assessment of the Estimations

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Abstract

Potential cost savings estimated from reduction of regional variation in Medicare spending are considerable but questioned. This article evaluates the validity of the principal methods that have been used in the estimations of the potential savings. Three estimation approaches were identified. The first approach uses adjusted expenditures to calculate avoidable costs, but adjusted expenditures can be independent of avoidable costs, and measurement errors are not controlled. The second approach uses an outcome variable to replace its causal factors, and is not acceptable because the association between the outcomes and the causes is untestable. The final approach uses surveys to directly measure physician beliefs and patient preferences, but the sole study using this approach is weakened by sample selection biases and incomplete controls. A development of reliable measures and a switch of observation from clinic settings to geographic contexts could make the estimations more convincing.

Keywords

validity, cost estimation, regional variation, professional practice style, Medicare spending

Introduction

Per capita expenditure in the Medicare Fee-for-Service (FFS) Program in one region can be more than twice that in other regions, and such variation has persisted for half a century (Cutler & Sheiner, 1999; Newhouse & Garber, 2013; J. E. Wennberg, Brownlee, Fisher, Skinner, & Weinstein, 2008; J. E. Wennberg & Gittelsohn, 1973, 1982). From the seminal body of work on regional variation in Medicare spending, the Dartmouth Group suggested that 20% to 30% of the spending can be saved by cutting spending in high-spending regions without reducing health care quality (Skinner & Fisher, 2010). The potential cost savings could influence policy makers' perceptions of health care delivery (Luft, 2012; Skinner & Fisher, 2010).

However, unlike the estimations of avoidable costs or potential cost savings from spending components of the U.S. health care system (Farrell et al., 2008; Fox, 2009; New England Healthcare Institute, 2008), there are no independent reports that have detailed the methodologies used in the cost estimations produced through observational research on regional variation. Questions regarding the validity of methods and associated results have therefore been raised (Bernstein, Reschovsky, & White, 2011; Grover, 2013; Rosenthal, 2012; Sheiner, 2013). Utilization of appropriate

estimation methods is crucial for production of valid and accurate estimations. In this review, we provide an assessment of the methods used in the estimations of potential cost savings from regional variation in Medicare spending.

Method

Data Sources and Study Selection

We searched PubMed and Web of Science for publications, the Medicare Payment Advisory Committee and the U.S. Congressional Budget Office for governmental reports, and the Dartmouth Atlas of Health Care, along with the National Bureau of Economic Research (NBER) and Acumen LLC, for research institute documents. We used keywords related to the concepts of regional medical cost, such as avoidable cost, region, and Medicare. Appendix Table A1 lists the detailed search terms and strategy.

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Table 1. Study Characteristics.

Study	Causes of avoidable costs	Statistical procedures	Benchmark	Estimated saving (%)	Statistical approach
Cutler and Sheiner (1999)	Not identified	Not specified	10% higher than the lowest region	15	Approach I
Skinner, Fisher, and Wennberg (2001)	Professional practice styles, patient preferences	Multivariable regression		20	Approach II
J. E. Wennberg, Fisher, and Skinner (2002)	Professional practice styles	Indirect standardization	The lowest decile	29	Approach I
J. E. Wennberg, Brownlee, Fisher, Skinner, and Weinstein (2008)	Professional practice styles	Indirect standardization	Specific regions	30-40	Approach I
MaCurdy et al. (2013)	Professional practice styles, patient preferences, unknown causes	Multivariable regression	Specific regions	7 or 20 ^a	Approach I
Cutler, Skinner, Stern, and Wennberg (2013)	Physician beliefs	Multivariable regression		17	Approach III

Note. See the main text for the descriptions of Approaches I, II, and III. FFS = Fee for Service.

^aAuthor's calculation ($= 100 \times \text{dollars of potential cost saving} / \text{Medicare FFS spending}$).

Publications, articles, and reports that contained the following elements met our selection criteria and were included in the review: (a) savings realized from regional variation in medical spending; (b) provision of original estimated figures; (c) description of estimation methodologies; (d) expenditures including, at a minimum, both Medicare hospital and physician reimbursements; (e) estimations based on regions in 50 states and the District of Columbia; (f) publication date from 1990 to 2013.

Data Synthesis and Analysis

The causes of avoidable costs were identified, and estimation approaches were synthesized. We assessed the approaches and their applications using statistical theories and, where possible, performed empirical examinations.

Results

Six studies met our selection criteria (Table 1). We found two published citations: one from Web of Science and one from PubMed (Cutler & Sheiner, 1999; J. E. Wennberg, Fisher, & Skinner, 2002). We found four unpublished citations: one from the Dartmouth Atlas of Health Care (J. E. Wennberg et al., 2008), two from NBER (Cutler, Skinner, Stern, & Wennberg, 2013; Skinner, Fisher, & Wennberg, 2001), and one from Acumen LLC (MaCurdy et al., 2013).

The potential savings estimated ranged from 7% to 40% (Table 1). We listed the potential savings estimated chronologically by the date the studies were issued. The first study estimated that Medicare expenditures could be reduced by 15% if high-spending regions were to practice at the level of 10% higher than the lowest region (Cutler & Sheiner, 1999). The second estimated that narrowing regional variation could have reduced Medicare expenditures by nearly 20%

(Skinner et al., 2001). The third demonstrated that if spending levels in the lowest decile were realized in all higher regions, total spending would have been cut by 29% (J. E. Wennberg et al., 2002). The fourth pointed out that setting the national spending level to match the benchmarks achieved by Mayo Clinic in Minnesota and Intermountain Healthcare in Utah could have reduced Medicare spending by 30% and 40%, respectively (J. E. Wennberg et al., 2008). The fifth estimated that Medicare could have saved US\$25 or US\$68 billion per year (approximately 7% or 20% of total FFS spending by author calculation) if utilization levels are set to that of St. Cloud, Minnesota, or Rochester, New York (MaCurdy et al., 2013). The last one stated that 17% of overall Medicare expenditures are due to physician beliefs and can be justified by clinical effectiveness (Cutler et al., 2013).

Among the citations, we found three causes of avoidable costs: professional practice styles, patient preferences, and unnamed causes. Practice style and patient preference describe professional and patient opinions about benefits of medical care, respectively. Unnamed causes are those that are believed to cause medical care waste but are not specified. Practice style was listed as a cause of avoidable costs in five citations, patient preference in two citations, and unnamed causes in one citation. One study did not specify any causes.

Three approaches, which we termed I, II, and III for expediency in discussions, are used in the estimations. In the following discussion, the three approaches and their applications are described and assessed separately because of considerable differences in estimation methods and unique challenges faced by each of them.

Approach I

This approach was used in four citations (Cutler & Sheiner, 1999; MaCurdy et al., 2013; J. E. Wennberg et al., 2008; J.

E. Wennberg et al., 2002). It calculates adjusted regional expenditures, sets a benchmark expenditure, and sums up adjusted expenditures exceeding the benchmark to be national potential savings. Comparisons of crude expenditures are often confounded by the differences in population illness. Standardization, a statistical method used in vital statistics and epidemiological research (Gordis, 2008), is used to exclude illness effects on crude expenditures, resulting in adjusted expenditures. Adjusted expenditure in the regions believed to be the most efficient is set as a benchmark. Creation of benchmarks rarely involves statistical estimations and thus is beyond this methodological review. We therefore only review the standardization method.

Theoretical assessment. Standardization provides a statistical correction of adjusting variables and retains measurement errors in adjusted expenditures (Appendix B). Adjusting variables generally consist of illness measures that reasonably contribute to medical spending. Except for adjusting variables, standardization does not demand that other variables be identified. The three causes, practice styles, patient preferences, and unnamed factors, are irrelevant in the calculation of adjusted expenditures. Adjusted expenditures can be independent or partially dependent on the three causes and thus are avoidable costs.

However, when medical services are viewed from clinical decision-making processes, any care for a medical condition is decided by medical professionals and patients. The costs of medical care thus rely on illness conditions and varied decision making as a result of professional practice styles, patient preferences, and unnamed factors. When illness is controlled and random measurement errors are negligible, only these three causes contribute to variation in medical expenditures. This might be the very logic upon which this approach is grounded.

If some known omitted covariates, or unadjusted variables, can reasonably explain variation in adjusted expenditures, then this approach may mistake unavoidable costs for avoidable costs. We thus have the following hypothesis:

Hypothesis 1: Variation in illness-adjusted expenditures does not depend on reasonable causes.

Random measurement errors exist universally and do not need an empirical test to confirm their existence. However, in small regions, due to the paucity of patients and random distributions of medical costs, measurement errors can be substantial. By contrast, measurement errors are small in large regions because of the normalization of random errors. Sizes of geographic units affect estimations, and so we have the following hypothesis:

Hypothesis 2: Random measurement errors in illness-adjusted expenditures do not depend on sizes of geographic units.

Empirical assessment. Our empirical testing is guided by three sources of variation in health care costs: health status, differential demand, and health market structure (Cutler & Sheiner, 1999; Fuchs, McClellan, & Skinner, 2001). Health status is measured by age, sex, and mortality rate. Currently, case mix measures such as hierarchical condition categories are widely used in measuring health status. These measures may not be reliable because of varied diagnostic and recording practices (Song et al., 2010). On the contrary, mortality rates are unambiguous and highly correlated with medical costs (Hogan, Lunney, Gabel, & Lynn, 2001; Riley & Lubitz, 2010). Differential demand is measured by median household income, race, and percentage of population with less than high school education and proportion of beneficiaries in Medicaid. The market structure is measured by medical care prices, hospital beds and physicians per 1,000 residents, percentage of medical specialties in the physician workforce, Health Maintenance Organization (HMO) penetration in the health insurance market, Medicare Advantage (MA) market share, Medicare population density, and rurality. Population density and rurality replaced population size used in the early studies (Cutler & Sheiner, 1999; Fuchs et al., 2001) because of the dependence of population sizes on areas covered.

We acquired Medicare data from the database published by the Dartmouth Atlas of Health Care (2013). The data include regional per capita expenditures that are adjusted by age, race, sex, and medical care price in the Medicare FFS program in 2004, 2005, and 2006, and regional social demographics in 2006. The expenditures are aggregated from 20% of Medicare claims data (approximately 5.3 million beneficiaries each year). As age, race, sex, and price effects have already been removed from the adjusted expenditures, these four variables are not included in our regression models.

We chose 2006 as the time frame of regression analysis because this year's data provide regional demographic variables. Furthermore, effects of risk selection of MA program on FFS spending could be relatively low because of rapid increases in MA market penetrations in recent years (The Medicare Payment Advisory Commission, 2012). To illustrate the effect of regional population sizes on the estimations, three multivariable ordinary least squares (OLS) regression models were fitted separately to 50 states and the District of Columbia (51 states), 306 hospital referral regions (HRRs), and 3,164 hospital service areas (HSAs). We also tabulate Pearson product-moment correlation coefficients (PPMCCs) of adjusted expenditures between years to illustrate the measurement errors.

Estimation results. The regression results (Table 2) show that most of the selected omitted covariates were statistically significant ($p < .05$) in the model for HSAs largely because

Table 2. Regression Results of Adjusted Medicare Expenditures.

Covariate	States (N = 51, CV = .112)	HRRs (N = 306, CV = .123)	HSAs (N = 3,416, CV = .171)
Logarithm of Medicare density	224.1*	335.9*	305.4*
Rurality (%)	-1.7	-6.8	0.6
Beds (per 1,000 residents)	703.0*	567.4*	299.5*
Physicians (per 1,000 residents)	-843.6*	-598.3*	-176.6*
Specialties (%)	28.1	50.4*	9.5*
FFS mortality (per 1,000)	579.4*	354.8*	452.3*
Medicaid (%)	-15.9	7.8	2.8
MA market share (%)	-118.9	-503.9	-569.1*
HMO penetration (%)	13.4	0.5	-3.1*
Less than high school (%)	26.6	3.4	17.8*
Household income (US\$1,000)	27.9	2.9	10.6*
R ²	.77	.61	.34

Source. The Dartmouth Atlas of Health Care (<http://www.dartmouthatlas.org/tools/downloads.aspx>).

Note. Expenditures are per capita—combined FFS reimbursements for hospital and physician services, adjusted by age, sex, race, and medical price. Density—Medicare beneficiaries per square mile. Rurality—percentage of beneficiaries living in rural area. MA market share—MA enrollment in Medicare enrollment. HMO penetration—HMO enrollment in insured population. CV—coefficient of variation in regional per capita—adjusted expenditures. HRR = hospital referral region; HSA = hospital service area; FFS = Fee for Service; MA = Medicare Advantage; HMO = Health Maintenance Organization.

*Statistically significant at $p < .05$.

large sample sizes impart greater statistical detection power. In the HSA model, the effects of median household income, percent of population with less than high school education, MA market share, and HMO penetration were statistically significant. In the HRR and HSA models, the effect of percentage of medical specialties in physician workforce was statistically significant. In all three models, hospital beds and physicians per 1,000 residents, mortality rates, and Medicare beneficiary density were also statistically significant.

Variation in adjusted expenditures differs by the sizes of geographic units (Table 2). Variation was lower among larger regions than among smaller ones (coefficients of variation were .11, .12, and .17 among states, HRRs, and HSAs, respectively). Small variation among large geographic units may be due to intravariation among subgeographic units, but more variance can be explained at the microlevel because of greater statistical detection power. However, by the same set of omitted covariates, R -squares were .77, .61, and .34 among states, HRRs, and HSAs, respectively. The R -square values represent 23% unexplained variation among states, 39% among HRRs, and 66% among HSAs.

Table 3. PPMCCs of adjusted Medicare Expenditures.

Year	2004	2005
States (N = 51, \bar{n} = 103,094)		
2005	.986	
2006	.986	.991
HRRs (N = 306, \bar{n} = 17,182)		
2005	.973	
2006	.954	.966
HSAs (N = 3,164, \bar{n} = 1,530)		
2005	.730	
2006	.706	.714

Source. The Dartmouth Atlas of Health Care (<http://www.dartmouthatlas.org/tools/downloads.aspx>).

Note. Expenditures are per capita—combined FFS reimbursements for hospital and physician services, and are adjusted by age, sex, race, and medical price. N is the number of geographic units. \bar{n} is average number of beneficiaries in 2006. All coefficients of correlation are statistically significant at $p < .05$. PPMCC = Pearson product-moment correlation coefficient; HRR = hospital referral region; HSA = hospital service area.

We further illustrated the measurement errors by PPMCCs of repeated measures (Table 3). A large PPMCC indicates small measurement errors. The average numbers of beneficiaries in 2006 were approximately 103,000, 17,000, and 1,500, respectively, among states, HRRs, and HSAs. Among the corresponding regions, PPMCCs between 2005 and 2006 were .99, .97, and .71. PPMCCs were smaller between 2004 and 2006 than between 2005 and 2006.

Comments. Numerous covariates omitted in adjustment have had significant impacts upon adjusted health care expenditures. Mortality rate is a measure of population health and needs adjusting in the first place. HMO management of clinical practice has a spillover effect upon FFS utilization (Baker, 1999). HMO penetration and MA market share can partially capture these spillover effects. Income and education positively contribute to medical expenditures. Physicians and hospital beds per 1,000 residents and proportion of medical specialties measure health care resource, and are believed to contribute to the formation of practice styles, but the magnitude of their contribution to avoidable costs is unknown.

Population density is a strong predictor of medical expenditures, and its implication has not been fully explored yet. It would be unreasonable to reject the effect of distance on care-seeking behaviors. When medical resources are evenly allocated by population size, seeking care in low population density areas is inevitably more difficult than in high density areas. New medical technologies are believed to be a major contributor to health care spending (Currie & Gruber, 1996; Cutler, McClellan, Newhouse, & Remler, 1998; Schneider, 1999). They are more likely to be affordable and utilized in medical research centers and large hospitals located in metropolitan areas. Furthermore, hospitals with a large volume of surgeries produce higher quality of care (Birkmeyer et al.,

2002; Dimick, Finlayson, & Birkmeyer, 2004). Quality improvement is also associated with areas with a higher concentration of health care workers and facilities.

Hypothesis 1 thus was rejected. Variation in illness-adjusted expenditures does depend on reasonable causes. It is plausible to attribute all medical costs caused by social gradients and population densities to avoidable costs. The exclusion approach also faces difficulty in separating the contribution of the three causes from that of other omitted covariates because there are usually no clear boundaries between them. Hypothesis 2 was also rejected. Uses of different geographic units of observation are likely to generate different estimates of potential savings.

In the four citations using this approach (Table 1), benchmarks can be a region or a group of regions, and their spending level can be set high or low. Health status or illness can be adjusted by social demographics or social demographics plus diagnoses. Those manipulations can affect sizes of estimated savings. But none of them can overcome the inefficiency inherent in this approach—uncertain dependence of adjusted expenditures on practice styles, patient preferences, and unnamed factors.

Approach II

By this approach, unmeasured causes—practice styles and patient preferences—are replaced by an outcome variable, end-of-life (EOL) visits that measures practice intensity, in a multivariable regression model (Skinner et al., 2001). The coefficient of the EOL visits is used to calculate expected regional expenditures when other independent variables in the model are fixed. The expected expenditure in the lowest regions of the EOL visits is set as an efficiency level; expected expenditures exceeding this efficiency level are avoidable costs.

Theoretical assessment. Approach II has its advantage over Approach I because a variable is explicitly used to catch the effects of stated causes in a regression model, and random measurement errors are captured by residuals (Appendix 3). But the substitution of causes by their outcomes can greatly threaten the estimation validity. The successful application of the approach relies on the condition that an outcome measure completely captures the effects of the stated causes and no others. Otherwise, the estimation would be biased because it may catch partial effects of stated causes, effects of other causes, or both. Practice styles and patient preferences are concepts with no associated measurements, and the difficulty lies in testing whether and how much variation in the EOL measure is explained by practice styles and patient preferences. In brief, there is no theoretical foundation that an outcome variable depends only on these two unmeasured causes.

In the regression models, both medical spending and number of EOL visits can be correlated with error terms. Number of EOL visits is a measure of medical

service utilization. Expenditures are calculated when the price of visits is factored into visits; and utilization is calculated when medical expenditures are divided by the price of medical care. Because number of EOL visits is a component of total medical utilization and monetized EOL visits is a component of total medical expenditure, variation in medical expenditures and variation in EOL visits could be caused by the same unmeasured variables.

Empirical assessment. The association between conceptual causes and outcome measures is empirically untestable. However, evidence has been reported that calls into question the validity of the underlying assumption of EOL measure as an outcome of professional styles and patient preferences (Bach, Schrag, & Begg, 2004; Kaestner & Silber, 2010; Neuberger, 2009; Romley, Jena, & Goldman, 2011). The measure has been criticized for ignoring variation in mortality risk, underlying causes of death, and care quality among patients at risk of death. The EOL measure as a substitute measure of practice styles and patient preferences is unlikely reliable, and so are the potential savings estimated.

Approach III

This approach, used in a recent study, surveys physicians' beliefs and patient preferences about intensive use of medicine, and estimates belief effects using multivariable regression models (Cutler et al., 2013). This study compiled responses of 516 cardiologists and 807 primary care physicians (PCPs) to clinical vignette questions in 64 large HRRs. It also surveyed 1,413 Medicare beneficiaries about their preferences for unneeded care and EOL care in hypothetical scenarios. In the models with measures of physician beliefs and patient preferences as independent variables, and age-, sex-, race-, and price-adjusted total expenditures as dependent variables, patient preferences explain little of regional variation in expenditures. Physician beliefs, measured by recommendations of intensive care, palliative care for the severely ill, and follow-up care beyond guidelines, explain a large amount of variation in Medicare expenditures. The study estimated that Medicare could save 36% of total EOL expenditures and 17% of total Medicare expenditures, as these expenditures are associated with physician beliefs that are unsupported by clinical evidence.

Theoretical assessment. As the article states, physician beliefs were used to predict medical spending for the first time (Cutler et al., 2013). This is a great accomplishment for Approaches I and II where causal factors are not measured and their effects cannot be directly estimated. However, the application of the approach in the sole study may be limited because of the weaknesses incurred in the survey and model specifications.

Physicians were not randomly selected. Medicare beneficiaries are served by more than 60 physician specialties and 10 other health care professional specialties (Medicare,

Table 4. Average Medicare FFS Expenditures and Market Conditions.

Tercile of Medicare beneficiary size	No. of HRRs	Average no. of Medicare beneficiaries	Average Medicare FFS expenditure (US\$)	Medicare population density (beneficiaries/mile ²)	MA penetration (%)		
					Average	Minimum	Maximum
National	306	110,485 (109,664)	7,258 (981)	60.6 (216.6)	14.1 (12.7)	0.0	54.7
Tercile							
1	102	33,860 (9,280)	7,018 (1,116)	23.7 (47.4)	5.3 (9.0)	0.0	48.8
2	102	75,623 (15,989)	7,071 (909)	49.6 (212.6)	10.3 (12.2)	0.1	45.3
3	102	221,973 (127,535)	7,369 (901)	88.3 (300.5)	16.8 (14.5)	0.1	54.7

Source. The Dartmouth Atlas of Health Care (<http://www.dartmouthatlas.org/tools/downloads.aspx>).

Note. Expenditures are per capita—combined FFS reimbursements for hospital and physician services, and are adjusted by age, sex, race, and medical price. Inside parentheses are standard deviations. FFS = Fee for Service; MA = Medicare Advantage; HRR = hospital referral region.

2014), but only PCPs (composed of four physician specialties) and cardiologists were surveyed. Small-area research does not support that there is a uniformed practice pattern among physician communities within a region (J. E. Wennberg, 1999). Evidence shows that the association of physician beliefs and intensive use of medical care is strong for some specialties and weak for others (Han et al., 2013). It is thus hard to judge whether the beliefs of PCPs and cardiologists can replace unstudied global beliefs of all medical professionals who bill Medicare. Furthermore, physician expenditures only account for 28% of total Medicare expenditures, and the remaining 72% is paid to hospitals, skilled nursing facilities, home health agencies, hospices, and durable medical equipment providers (The Dartmouth Atlas of Health Care, 2013). It is uncertain how those five specialties of physicians affect medical care provided by those institutions.

The survey was carried out in large HRRs. Larger HRRs are mostly located in large metropolitan areas where population densities, socioeconomic conditions, and medical industries can differ from small HRRs. Furthermore, MA penetrations are higher in larger regions than in smaller ones (Song, 2014). Risk selections of MA plans could affect FFS expenditures more in larger regions than in smaller ones, and these selection effects are not controlled.

In the regression models, only physician beliefs and patient preferences are present as independent variables. The statistical models are built upon the assumption that beliefs and preferences unconditionally affect medical spending, which may not be supported by survey methodologists (Alreck & Settle, 2013). It has been found that broader contexts such as population sizes, medical care supplies, sociodemographics, and population mortality rates are associated with medical spending (Cutler & Sheiner, 1999; Fuchs et al., 2001). It is plausible that beliefs and preferences can supersede illness and those contextual variables.

Empirical assessment. We tested whether region selections is biased in this study. We acquired Medicare FFS expenditures and Medicare enrollments in 2005, the year when the survey

was conducted (the Dartmouth Atlas of Health Care, 2013). We grouped HRRs into terciles by the number of total Medicare beneficiaries (Table 4). In the lower, middle, and upper tercile, average number of beneficiaries were 34,000, 76,000, and 222,000, respectively; Medicare population densities were 23.7, 49.6, and 88.3 beneficiaries per square mile, respectively; and MA penetrations were 5.3, 10.3, and 16.8%, respectively. In the upper tercile, MA penetrations among HRRs ranged from 0.1% to 54.7%. The cost shifting between the MA and FFS programs could affect FFS spending more in large HRRs than in small ones, and the impact could differ greatly among large HRRs. A sample composed of large HRRs thus may be nationally nonrepresentative and biased.

Discussion

We identified three statistical approaches used in the estimations of potential savings from reduction in regional variation in Medicare FFS spending. Those approaches were evaluated separately by statistical theories and, when possible, by empirical tests. Approach I uses standardization methods, lacks credit in inferential statistics, and cannot separate avoidable costs, unavoidable costs caused by certain omitted covariates, and measurement errors. Approach II may be stronger but is limited because of ambiguous associations between an outcome variable and stated causes. Approach III overcomes the weaknesses of the two former approaches, but its application in the sole study may not be fully credible because of sample biases and model specification issues.

Potential cost savings are important parameters that can assist policy makers in understanding the potential return of health reform efforts. An underestimation of the savings could lead to missing the full scope of cost controls, and an overestimation could be misleading as well. Because waste in Medicare spending among regions is largely believed to be generated by professional practice styles, an overestimation could impose unjustifiable pressure on medical practitioners.

Physician practice was hypothesized as one of the major causes of regional variation in individual surgical procedures in the 1930s (Glover, 1938). However, measurement of practice styles has never been popular in regional research. There are some studies that measure practice styles, but the measurement is restricted to a handful of physician specialties (Epstein & Nicholson, 2009; Escarce, 1993; Han et al., 2013; Komaromy et al., 1996; Lucas, Sirovich, Gallagher, Siewers, & Wennberg, 2010; Matlock et al., 2010; D. E. Wennberg et al., 1997). This may be due to survey costs and difficulties in acquiring dependable measures of professional styles or beliefs because surveys are prone to inconsistencies between answers and true feelings, nonresponse, unrepresentative sample, question wording, and so on (Alreck & Settle, 2013). Most importantly, reactive effects such as social desirability can also occur (Heppner, Kivlighan, & Wampold, 2008). Nevertheless, as long as physician styles or beliefs are hypothesized to be a major cause of waste in medical spending, they should be measured properly.

Measurement of population illness also needs to be refined. In most of the citations, demographics such as age, sex, and race are used to capture population illness. However, demographic variables explain a very small amount of regional variation in Medicare spending (Cutler & Sheiner, 1999; Fuchs et al., 2001). Certain diagnoses can explain up to 50% of the variation (Sheiner, 2013). Diagnoses can be inflated in high-spending regions because extra diagnostic testing is carried out in those regions (Song et al., 2010), making diagnoses unreliable measures of population illness. However, there is no evidence that demographics can completely capture population illness. Mortality rates have been found to be associated with medical spending (Fuchs et al., 2001), but medical spending can possibly contribute to longer survival. Varied MA penetrations and MA risk selection complicate measurement of illness in the FFS program even more (Song, 2014).

Patient preference, either served as a causal factor or as a control in the estimations of potential savings, is an essential factor, and its importance has been revisited in recent studies. The most recent citation in this review found that as high as 72% of surveyed Medicare beneficiaries want unneeded tests and 56% want unneeded referrals to cardiologists (Cutler et al., 2013). Patient preferences also have been found to contribute significantly to regional variation in Medicare spending (Baker, Bundorf, & Kessler, 2014). In estimating potential savings, patient preferences and professional practices are usually treated to be independent of each other. This independence may not be supported by ecological perspectives in geographic research (Stokols, Lejano, & Hipp, 2013), which emphasize the interactions between patients and physicians. Evaluation of patient effects may deserve further investigation.

Certain factors are not considered in the estimations of potential savings but realized or found in empirical studies (Rosenthal, 2012). For example, population sizes and

densities are associated with Medicare spending (Cutler & Sheiner, 1999; Fuchs et al., 2001; Song & Shi, 2016). It is generally believed that fairness of medical resource distribution can be judged by resources per capita, which could imply that uneven distribution of resources per square mile may be socially acceptable. Medical spending in Medicare is weakly associated with that in Medicaid and employment health insurance (Chernew, Sabik, Chandra, Gibson, & Newhouse, 2010; Cuckler et al., 2011; Martin et al., 2007). Medical spending in the traditional Medicare FFS program, which is examined by the three approaches, can be influenced by the penetrations of MA program (Song, 2014).

In brief, the estimation of medical waste resulting from regional variation could significantly benefit from improved measurement of causal factors. But a focus on measures alone may not completely solve the estimation issues discussed earlier. The correct use of statistical approaches relies on the understanding of causal mechanisms under which a phenomenon is studied. The three approaches are used largely under an assumption that regional variation in medical spending is created in clinic settings where professional practice and patient preference dominate. And regions are merely chosen as units of study. However, this assumption is challenged by the findings that regional social-physical environments contribute to the variation in medical practices.

Those findings call for a broader observation that has been long emphasized by human geography, which studies the nature, production, and reproduction of places and spaces (Johnston, 2000). Economic geography, a subfield of human geography, suggests that economic practices are embedded within geographic contexts, networks, and institutional structures, all in relation to spatial scales (Bathelt & Gluckler, 2003; Yeung, 2005). The estimation of medical waste could be more convincing when medical practices are observed from socioeconomic and geographic contexts.

Research in human geography also points out that certain regional properties such as population densities and sizes are not easily manipulated because they are produced by more fundamental qualities such as natural environments and resources (Fonseca & Wong 2000; Stokols et al., 2013). On the contrary, distribution of medical technologies and resources, cultural beliefs and values toward the utilization of health care, and physician practices could be more responsive to policy changes. Clarification of long-run and short-run cost savings could also make policy solutions more efficient.

Study Limitations

Assessing the estimations of potential saving on the basis of information unpublished was very challenging, and the literature review was limited by acquisition of the original studies. We may have excluded studies from unpublished sources. Different units of analysis, expenditure measures, selections of covariates, or statistical methods could have led

to different interpretations of the results in the empirical evaluation. Human geography could possibly shed light on the estimations of potential savings, but research on medical care spending from this perspective is scarce. The paucity of essential information on geographic dynamics behind regional variation could prevent us from a comprehensive evaluation of the estimation methods for the potential saving.

Conclusion

The estimates of potential cost savings from reducing regional variation in Medicare FFS spending are not appropriate either due to inappropriate methodologies or incorrect application of statistical methodologies. A lack of reliable measures of major causal factors and a sound theoretical framework appears to be the key issue. Future regional research should continue refining the measurements of covariates, such as practice styles, patient preferences, and population illness, and examine the effects of contextual features, such as the population densities, sizes of living place, resources, cultural beliefs, and values toward the utilization of health care.

Appendix A

Literature Search Strategy

Table A1. Search Strategy.

Search	String
#1	Regional
#2	Region
#3	Area
#4	#1 or #2 or #3
#5	Spending
#6	Cost
#7	Expenditure
#8	#5 or #6 or #7
#9	Medicare
#10	Fee for Service
#11	FFS
#12	#9 and (#10 or #11)
#13	Saving
#14	Avoidable
#15	#12 or #14
#16	#4 and #8 and #12 and #15
–	Documentation date from January 1, 1990 to December 31, 2013

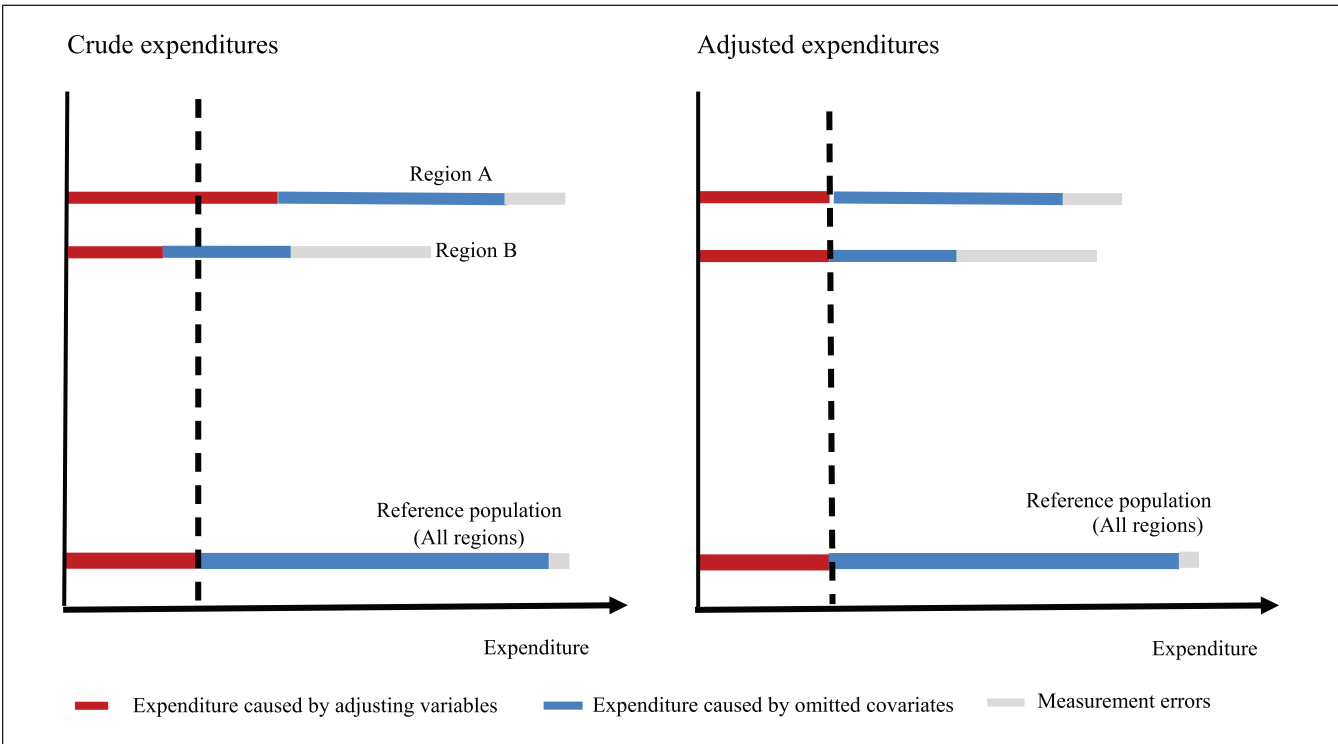


Figure A1. Theoretical partitions of crude and adjusted regional per capita expenditures.
Note. Measurement errors can be negative.

Appendix B

A Theoretical Discussion of Standardization

Theoretically, a crude regional expenditure consists of three components (Figure A1): the contribution of adjusting variables, the contribution of omitted covariates, and measurement errors. Adjusting variables are those for which effects are corrected. Omitted covariates, either measurable or unmeasurable, contribute to variation but are not used in standardization. Practice style, patient preference, and unknown causal factors can be examples of unmeasured omitted covariates. Each of the three components can contribute to crude medical expenditures.

An adjusted expenditure still contains these three components, but standardization forces the contribution of adjusting variables to be as equal as possible among regions. With a complete adjustment, variation in adjusted expenditures can only be caused by omitted covariates and measurement errors.

A variety of standardization methods attempt to eliminate the variation caused by adjusting variables. Standardization can be easily implemented by most statistics programs and are widely used in variation documentation. In many instances, standardization methods are not mentioned. Of four citations that used standardization to acquire adjusted expenditures, two used indirect methods, one used regression method, and one citation did not report standardization methods (Cutler & Sheiner, 1999; MaCurdy et al., 2013; J. E. Wennberg, Brownlee, Fisher, Skinner, & Weinstein, 2008; J. E. Wennberg, Fisher, & Skinner, 2002). But given the purpose of standardization, three popular methods—direct, indirect, and regression methods—can adequately illustrate how the contribution of adjusting variables are equalized among regions, and the contribution of omitted covariates and measurement errors are carried over to adjusted expenditures.

Direct and indirect methods. Direct and indirect methods remove the effects of population structures on variation in medical expenditures (Gordis, 2008). The methods are based upon a reference population, usually the total population studied. This reference population is stratified into $S(1, 2, \dots, j, \dots, S)$ subpopulations by categorized adjusting variables and so is the population in each region $(1, 2, \dots, i, \dots, R)$

$$\tilde{e}_i = \frac{\sum_{j=1}^S (\bar{e}_{ij} \times N_j)}{\sum_{j=1}^S N_j} \quad (1)$$

Direct method first calculates crude per capita expenditures \bar{e}_{ij} in subpopulation j of region i and then applies them to the subpopulation N_j of the reference population. Adjusted expenditure \tilde{e}_i of region i is calculated in Equation 1. The contribution of adjusting variables is neutralized by applying the reference population structure to all regions. The contribution of omitted covariates and measurement errors are transferred by the crude per capita expenditures \bar{e}_{ij} to adjusted per capita expenditure \tilde{e}_i .

$$\tilde{e}_i = \frac{t_i}{e_i} \times \bar{E} = \left[\frac{\sum_{j=1}^S (\bar{E}_j \times n_{ij})}{\sum_{j=1}^S n_{ij}} \right] \times \bar{E} \quad (2)$$

Indirect method utilizes a different strategy to remove the effects of adjusting variables (Curtin & Klein, 1995; Mantel & Stark, 1968). Adjusted expenditure \tilde{e}_i is calculated from the total crude expenditure t_i in region i , an expected total expenditure e_i by applying per capita expenditure \bar{E}_j in the subpopulations of the reference population to the subpopulation n_{ij} in the region, and per capita expenditure \bar{E} in the reference population. The contribution of adjusting variables is neutralized by the expected total expenditure e_i . The contribution of omitted covariates and measurement errors are carried over by regional crude expenditures t_i in the denominator.

Regression method. Expenditures e_{ik} at patient level (i is a region that has n_i patients, and k is the k th patient in the region) are regressed on adjusting variables X_{ik} from the data of the total population (MaCurdy et al., 2013).

$$e_{ik} = \beta X_{ik} + \mu_{ik} \quad (3)$$

$$\tilde{e}_i = \bar{E} + \frac{\sum_{k=1}^{n_i} \mu_{ik}}{n_i} \quad (4)$$

The portion explained by adjusting variables is dropped from the calculation of adjusted expenditures. The residuals μ_{ik} , which are not explained by adjusting variables, are retained. The adjusted per capita expenditure \tilde{e}_i of a region is the sum of the average expenditure \bar{E} in the standard population and the average residual $\frac{\sum_{k=1}^{n_i} \mu_{ik}}{n_i}$ in that region.

As residuals do not contain contributions of adjusting variables and the average expenditure of the total population is a fixed number for all regions, variation in adjusted expenditures will not depend on adjusting variables but on residuals that capture the contribution of omitted covariates and measurement errors.

Regardless of standardization methods used, adjusted expenditures contain unvaried or slightly varied contributions of adjusting variables, contributions of omitted covariates, and measurement errors.

Appendix C

The Development of Approach II

Approach II, by which potential savings from reduction of regional variation was estimated, developed in an investigation of the impact of Medicare expenditures on the survival of Medicare beneficiaries (Skinner, Fisher, & Wennberg, 2001). In the estimation of expenditure effects on survival, a

naïve estimator, such as an ordinary least squares (OLS) regression, provides a biased estimate of expenditure effects because of the reverse causality problem—sicker populations spend more on health care. An instrumental variable and two-stage least squares are used to overcome the bias of the naïve estimators.

Physician visits in the last 6 months of life (end-of-life [EOL] visits) is selected as an instrumental variable. The investigators argue that practice styles and patient preferences generate varied health care intensities (Skinner et al., 2001). Decedents in the last 6 months of life are equally healthy because they all progressed to death within the same time frame. However, medical services in the last 6 months of life vary widely. Therefore, EOL measurement is not correlated with population health but with health care intensities.

There can be many EOL measures, but not all of them can be used as an instrumental variable. The investigators confirmed that EOL visits are correlated with some of the exogenous covariates in their models but not with the linear combination of the exogenous covariates, so it meets the less stringent condition of an instrumental variable (Skinner et al., 2001).

In the first-stage linear OLS regression, Medicare expenditures are regressed on EOL visits and a set of exogenous covariates such as chronic disease, poverty level, education, social security income, obesity, and living condition. The coefficient of EOL visits are used to predict Medicare expenditures in each of 306 hospital referral regions (HRRs). HRRs are grouped into deciles by average EOL visits. Potential savings are calculated as a sum of the differences between predicted expenditures in the lowest and the other deciles.

EOL visit serves as an instrument for medical expenditures in the two-stage regressions, but it does not in the estimation of potential savings that do not need the second stage of regression. As a covariate, EOL visits directly enters the first stage of OLS regression, and its coefficient is used to predict regional expenditures. Practice styles and patient preferences are the causes, and health care intensity, measured by EOL visits, is the outcome. Causes are replaced by their outcome in a regression model.

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