Geographic Adjustment of Medicare Payments to Physicians: Evaluation of IOM Recommendations

July 2012

Thomas MaCurdy
Jason Shafrin
Thomas DeLeire
Jed DeVaro
Mallory Bounds
David Pham
Arthur Chia

Acumen, LLC
500 Airport Blvd., Suite 365
Burlingame, CA 94010

[This page is intentionally left blank.]

EXECUTIVE SUMMARY

Medicare pays physicians for their services according to the Physician Fee Schedule (PFS), which specifies a set of allowable procedures and payments for each service. Each procedure is interpreted as being produced by a combination of three categories of inputs: physician work (PW), practice expense (PE), and malpractice insurance (MP). The particular blend of PW, PE, and MP inputs assessed to produce a service specifies its composition of relative value units (RVUs). A payment for a procedure depends on its assigned RVUs and the input prices assessed for each RVU component. Under mandates in Section 1848(e) of the Social Security Act, the Centers for Medicare and Medicaid Services (CMS) must apply geographic cost indices in the calculation of component RVU input prices. In 1992, CMS introduced Geographic Practice Cost Indices (GPCIs) to comply with this mandate; CMS updates GPCIs at least every three years.

In its latest efforts to improve the methodology and data sources used to compute GPCIs and other geographic input cost adjustments, CMS funded an Institute of Medicine (IOM) study to identify areas where the GPCI methodology could be improved. In its 2011 Phase I report, IOM evaluates the methodology CMS uses to make adjustments to the PFS and the extent to which alternative sources of data are representative of the economic circumstances healthcare providers face. The IOM study also offers a number of proposed modifications to the methodology CMS uses to compute GPCI values. This report evaluates IOM's recommended changes to the GPCI methodology.

How GPCIs Affect Physician Payments

GPCIs measure geographic differences in input prices. Paralleling the RVU structure, GPCIs are split into three parts: PW, PE, and MP. Each of these three GPCIs adjusts its corresponding RVU component. GPCIs do not affect aggregate payment levels; instead, they reallocate payment rates to reflect regional variation in relative input prices. For example, a PE GPCI of 1.2 indicates that practice expenses in that area are 20 percent above the national average, whereas a PE GPCI of 0.8 indicates that practice expenses in that area are 20 percent below the national average. CMS calculates the three GPCIs for payment areas known as Medicare localities. Each physician payment locality is assigned an index value, which equals the area's estimated input cost divided by the average input cost nationally. Localities are defined alternatively by state boundaries (e.g., Wisconsin), metropolitan statistical areas (MSAs) (e.g., Metropolitan St. Louis, MO), portions of an MSA (e.g., Manhattan), or rest-of-state areas that exclude metropolitan areas (e.g., Rest of Missouri). As a result, some localities are large metropolitan areas, such as San Francisco and Boston, whereas many localities are statewide payment areas that include both metropolitan and nonmetropolitan areas, such as Minnesota, Ohio, and Virginia.

Across these localities, CMS uses the conversion factor (CF), to calculate the payment for each service in dollars. The conversion factor, which is updated annually, indicates the dollar value CMS assigns to an RVU. The equation below demonstrates how CMS combines the CF with the PW, PE, and MP GPCIs and the corresponding RVUs to establish a Medicare physician payment for any service *H* in locality *L*:

$$Payment_{H,L} = [\underbrace{(GPCI_{PW,L} \times RVU_{PW,H})}_{\boxed{\text{Physician Work}}} + \underbrace{(GPCI_{PE,L} \times RVU_{PE,H})}_{\boxed{\text{Practice Expense}}} + \underbrace{(GPCI_{MP,L} \times RVU_{MP,H})}_{\boxed{\text{Malpractice Insurance}}}] \times CF$$

CMS calculates GPCIs using six component indices. Whereas the PW and MP GPCIs are based on a single component index, the PE GPCI is comprised of four component indices (i.e., the employee wage; purchased services; office rent; and equipment, supplies and other indices). The PE GPCI is calculated as a weighted average of the four PE GPCI component indices, where the weight assigned to each PE GPCI component index equals each input's average share of physician practice expenses nationally. Table 1 below provides additional information on each component index.

Table 1: Breakdown of GPCIs into Six Component Indices

GPCI	Component Index	Measures Geographic Differences in:
Physician Work	Single Component	Physician wages
Practice Expense	*Employee Wage*	Wages of clinical and administrative office staff
	Purchased Services	Cost of contracted services (e.g., accounting, legal, advertising, consulting, landscaping)
	Office Rent	Physician cost to rent office space
	Equipment, Supplies, and Other	Practice expenses for inputs such as chemicals and rubber, telephone use and postage
Malpractice	Single Component	Cost of professional liability insurance

Although GPCIs affect payments for each procedure depending on the relative amounts of PW, PE, and MP RVUs, one can summarize the overall impact of the GPCI components on a locality's physician reimbursement levels, using the Geographic Adjustment Factor (GAF). The GAF is calculated as the weighted average of the three GPCIs, where the weights are the percentage of RVUs nationally made up by the PW, PE, and MP RVUs. For calendar year (CY) 2012, one can calculate the GAF as follows:

$$GAF_L = (GPCI_{PW,L} \times 0.48266) + (GPCI_{PE,L} \times 0.47439) + (GPCI_{MP,L} \times 0.04295).$$

Overview of IOM's GPCI Recommendations

IOM recommended alterations of GPCIs fall into five broad categories shown in Table 2. The first column lists the recommendation category, the second column identifies the recommendation numbering system from IOM's report, and the third presents a brief description of these recommendations. Whereas the first three recommendation categories propose changes to the current GCPI methodology, the latter two endorse aspects of the current CMS approach. This report focusses on evaluating the potential impacts of the first three categories of IOM recommendations that propose revisions to the current methods for calculating GPCIs.

Table 2: IOM Geographic Practice Cost Index (GPCI) Recommendations

Category	Number	Description
Employee Wages	2-1	The same labor market definition should be used for both the hospital wage index and the physician geographic adjustment factor. Metropolitan statistical areas and statewide non-metropolitan statistical areas should serve as the basis for defining these labor markets.
	2-2	The data used to construct the hospital wage index and the physician geographic adjustment factor should come from all healthcare employers.
	4-1	Wage indexes should be adjusted using formulas based on commuting patterns for healthcare workers who reside in a county located in one labor market but commute to work in a county located in another labor market.
	5-4	The practice expense GPCI should be constructed with the range of occupations employed in physicians' offices, each with a fixed national weight based on the hours of each occupation employed in physicians' offices nationwide.
	5-5	CMS and BLS should develop a data use agreement allowing the Bureau of Labor Statistics to analyze confidential BLS data for CMS.
Physician Wages	5-2	Proxies should continue to be used to measure geographic variation in the physician work adjustment, but CMS should determine whether the seven proxies currently in use should be modified.
	5-3	CMS should consider an alternative method for setting the percentage of the work adjustment based on a systematic empirical process.
Office Rent	5-6	A new source of data should be developed to determine the variation in the price of commercial office rent per square foot.
Purchased Services	5-7	Nonclinical labor-related expenses currently included under PE office expenses should be geographically adjusted as part of the wage component of the PE.
Cost Share Weights	5-1	GPCI cost share weights for adjusting fee-for-service payments to practitioners should continue to be national, including the three GPCIs (work, practice expense, and liability insurance) and the categories within the practice expense (office rent and personnel).

Although not to become a part of IOM's formal recommendations until its Phase II report, a theme guiding recommendations throughout IOM's Phase I report is the development of a three-tiered system for defining payment areas: the first tier consists of counties to be used as the basis for calculating employee wage indices with adjustments incorporated to account for workers' commuting patterns across MSAs; the second tier comprises MSA-type areas to be used for the geographic cost adjustments of PE GPCI components such as office rents, purchased services, and malpractice insurance; and the third tier consists of a national payment area for PE GPCI items as "Equipment, Supplies and Other." Table 3 presents an overview of IOM's suggested replacements of current GPCI localities by payment areas tailored to capture the market environments appropriate for determining payment of individual GPCI components. The rows of this table list the six individual GPCI components incorporated in the PFS and the columns list the regions entertained as candidates for calculating geographic adjustments of payments to physicians. Readers may know the "statewide tier" payment area, which combines counties into tiers within each state based on each county's GAF value, as the "Option 3" payment area definition presented in the July 2007 proposed rule. Returning to the table, an "*X*" in a row indicates that the payment area suggested by IOM to compute the GPCI component. One sees in this table that IOM favors MSAs as the principal choice for payment areas, with counties playing a role for employee wage indices and a national market for equipment and supplies. The empirical analyses in later sections assess the impacts of considering each of the payment area candidates listed in Table 3, with the goal of placing the IOM recommendations in useful context.

Table 3: IOM's Suggested Three-Tiered System for Defining GPCI Payment Areas

GPCI Expense Category	**Payment Area**				
	County	***MSA***	***Statewide Tier***	***Locality***	***National***
Physician Work		**X**			
Practice Expense					
Employee Wage	**X**				
Purchased Services		**X**			
Office Rent		**X**			
Equipment, Supplies, Other					**X**
Malpractice Insurance		**X**			

Evaluation of IOM Recommendations for the Employee Wage Index

IOM proposes two notable changes to the current employee wage index (EWI) methodology. First, IOM recommends redefining the payment areas CMS uses to calculate EWI values. Second, IOM proposes that CMS measure worker wages within these payment areas using data limited to workers employed in the healthcare industry (rather than across all industries).

IOM Recommendations to Redefine Payment Areas for the Employee Wage Index

IOM's proposal for revising payment areas would permit EWI values to vary across counties, including for counties located in the same MSA. If implemented, the number of EWI payment areas would increase from 89 to potentially over 3,000. There exists substantial variation in employment costs within each of the current 89 locality-based payment areas. To adjust for this variability, IOM suggests calculating wage rates based on MSA data and inferring wage rates for counties through smoothing algorithms that account for computing patterns from counties to MSAs. This recommendation for GPCI wage calculations matches that proposed by IOM for the hospital wage index (HWI).

Four steps characterize IOM's proposals for calculating EWI values for each physician practice:

(1) Compute the mean/median hourly wage (*MHW*) for each MSA;
(2) Calculate an area index wage for each county based on out-commuting patterns;
(3) Assign an index wage to each physician office based on its county location; and
(4) Normalize physician office wage measures to create the employee wage index.

To illustrate these steps, consider a simple example shown in Table 4. In this example there are two physician practices; Physician Office *1* is located in County *A* in MSA *a*, and Physician Office *2* is located in County *B* in MSA *b*. Step 1 estimates the median/mean wage for each MSA. This step essentially replicates the current employee wage index methodology, but calculates a wage index value at the MSA rather than the locality level. Since this example only has one physician office in each MSA, each MSA's median wage equals the physician office wage. The sixth column of Table 4 displays the *MHW* as calculated under step 1 for each MSA.

Table 4: Example Application of the IOM Out-Commuting Adjustment

Physician Office	Physician Office Wage	Worker County of Residence	MSA where Worker is Employed	County-to-MSA Out-Commuting Shares	Current EWI Median Hourly Wage (*Step 1*)	IOM EWI Commuting-Adjusted Index Wage (*Steps 2, 3*)
1	$30	A	a	80%	$30	$28
			b	20%		
2	$20	B	a	20%	$20	$22
			b	80%		

Step 2 applies a commuting-based smoothing adjustment to create area index wages for each county. Specifically, the county wage indices equal a weighted average of the *MHW* values calculated in Step 1, where the weights are county-to-MSA *out-commuting* patterns. IOM's out-commuting-based weights are defined as the share of workers who live in a county where the physician office is located who commute out to work in a physician office in another MSA. This modification differs from an *in-commuting* adjustment, which is based on the share of workers who are employed at physician offices (or areas where offices are located) who commute from other areas. The fifth column of Table 4 displays the county-to-MSA out-commuting shares, and the seventh column presents each county's commuting-adjusted area index wage. One can calculate IOM EWI values for County *A*, for instance, as: \$30×80% + \$20×20% = \$28; for County *B*, the calculation is \$30×20% + \$20×80% = \$22.

Step 3 sets each physician office's wage measure equal to the Step 2 area wage of the county in which the office is located. Because the out-commuting adjustment envisioned by IOM in Step 2 varies by county, employee wage index values—and thus the PE GPCI as a whole—also potentially vary by county depending on the smoothing option chosen.

Paralleling the current EWI methodology, Step 4 normalizes out-commuting-adjusted wage measures by dividing each physician's wage measure by the PE RVU-weighted average wage measures for all offices. Although not shown in this example, this step produces an index whose PE RVU-weighted average value equals 1.

Through the use of out-commuting shares to weight the wages of physician office employees across MSAs, IOM's proposal redefines the EWI to measure the wage levels associated with the workers who live in a county rather than the workers who are employed in the county. The purpose of a wage index, however, is to measure the earnings of healthcare workers employed in a county, for this represents the costs of labor faced by the providers who hire in the county. The relevant input price physician practices must pay to compete in their pertinent labor market depends not only on the wage levels of individuals living nearby but also on the wage levels paid to attract individuals living outside the local area who work at the practices. As shown in this report, the values of the wage indices associated with healthcare workers living in a county verses the workers employed in a county can be quite different.

Moreover, the IOM smoothing adjustment can produce counterintuitive EWI values, especially in cases where a large share of workers commute from one MSA to another. Even if all practices in a county pay their workers an identical wage, the IOM method increases these practices' EWI values above that wage if workers living in that county commute to MSAs where practices pay higher wages. The reverse is true if workers living in this county commute to MSAs where practices pay lower wages. Further, in the extreme case where all workers in a county out-commute to another MSA, the EWI for physician practices in that county depends entirely on the wage levels paid by practices located in other MSAs.

When IOM's approach is applied in practice, this report concludes that IOM's out-commuting adjustment does reduce the size of cliffs. For counties in different localities that are located within 50 miles of one another, applying the smoothing algorithm to the employee wage index reduces the differences in GAF values by 0.14 percentage points (i.e., 0.0014) relative to the MSA payment area definition without smoothing. Although the magnitude of this change is small, recall that the IOM recommendation only applies the smoothing algorithm to the employee wage index, and the employee wage index constitutes only 19 percent of the total GAF value. Applying the smoothing methodology marginally reduces the frequency with which nearby counties have GAF differentials exceeding 5 percentage point. Thus, not only does the average difference in GAF values decrease for counties located close to one another, but the share of counties with large cliffs also decreases.

IOM Recommendations for Measuring Employee Wages

IOM's proposal to measure wages for workers using data from the healthcare industry rather than from all industries offers a number of conceptual advantages and disadvantages, but it would likely have little effect on GAF values. An obvious attractive feature of such a change in data sources relates to capturing geographic variation in worker wages that is idiosyncratic to employment in the healthcare industry. On the other hand, the IOM approach has two drawbacks. First, limiting the wage estimates to workers in the healthcare industry reduces the sample size and thus decreases the precision of the wage estimates. This issue is particularly relevant when measuring wages in sparsely populated rural areas. Second, measuring healthcare industry wages across different geographic areas using BLS OES data requires access to confidential BLS OES data, which may be difficult to acquire and would reduce the transparency of the GPCI methodology as providers would not have access to these data. Nevertheless, IOM's own calculations indicate that the correlation between all-industry and healthcare industry wages is over 0.99. Thus, despite certain conceptual arguments that favor calculating the employee wage index using healthcare worker wage data, the impact on GAF values is likely small in practice.

Evaluation of IOM Recommendations for Physician Work GPCI

Current policy methodology calculates the PW GPCI index following four steps:

(1) Select proxy occupations to include in the PW GPCI index and calculate an occupation-specific county-level index for each county;
(2) Assign weights to each proxy-occupation index based on the occupation's national share of wage bill;
(3) Apply 25 percent adjustment through the 'inclusion factor' to dampen responsiveness of the PW GPCI to regional variation in the proxy-occupation index; and
(4) Adjust values to ensure budget neutrality.

Table 5 summarizes the key changes in the above steps recommended by IOM. IOM's principal proposal consists of computing PW GPCI based on a familiar regression framework. Regarding Step 1, IOM endorses continued use of proxy occupations to measure regional variation in physician wages, but suggests selecting them based on the goodness-of-fit and predictive information conveyed by regression estimation statistics. With respect to Step 2, IOM recommends weighting each occupation according to the value of its estimated regression coefficient. For Step 3, IOM proposes an inclusion factor equal to the sum of the regression coefficients on the proxy occupation variables. IOM's Step 4 is identical to the status quo approach.

Table 5: Summary of Changes to PW GPCI Components

PW GPCI Component	Current PW GPCI	IOM's Recommendations
Proxy Occupations	Seven occupational groups intended to measure wages for professional workers	Can use current or an alternative set of proxy occupations
Occupation Weights	National wage shares	Correlation with physician wages
Inclusion Factor	25%	Sum of regression model's coefficients for the proxy occupations variables
Budget Neutrality Adjustment	Normalize index so that PW RVU-weighted average PW GPCI equals 1.0	Normalize index so that PW RVU-weighted average PW GPCI equals 1.0

Whereas the current construction of PW GPCI essentially relies on price index theory familiar throughout the policy community to measure price (and wage) differences across regions and over time, the IOM suggested approach creates an index based on the predicted values from a regression. The regression estimates implicitly produce shares for occupations in the index that correspond to no interpretable market basket. Instead, the coefficient estimates reflect the degree of correlations between the price of one labor commodity and the prices of others across regions. The coefficients cannot be interpreted as shares; any individual share (coefficient) can be negative or greater than one; the empirical findings presented in this report reveal many instances of both these cases.

While difficult to interpret IOM's PW GPCI as characterizing a classic form of a wage index, the IOM approach nevertheless has a straightforward statistical interpretation as a prediction of the relative regional wages of physicians forecasted using the relative regional wages of comparable occupations. Of course, if the wages of the group of occupations deemed to be related to physicians shift uniformly across regions, then all wage indices produce the same findings, since the form of weighting does not matter. However, when non-uniform shifts occur, then the form of weighting effects the values of indices and one must select which form best capture the phenomena of interest. From an economics perspective, a regression model that relates wages in regional markets mimics a reduced form specification with coefficients that summarize the impacts of a wide range of market factors determining wages, including differences the relative supplies and demands of occupations across regions, regional variation in the number of hours various occupations work, and composition of specialists in each area. Notwithstanding, if one interprets the goal of the PW GPCI as principally predicting regional differences in physician wages regardless of the sources of variation, then the IOM candidate offers a popular statistical candidate.

An empirical application of a variant of the IOM regression specification using BLS OES data reveals the following findings:

- All regression specifications produce a wide range of coefficient values, including a large number of negative values;
- The regressions produce few coefficients that are statistically significantly different from zero;
- The R-squared measure of fit for the various models varies from 0.19 to 0.65, depending on the diversity and number of MSAs included as observations in the regression; and
- The estimated IOM inclusion factor is near zero or negative.

The last finding in this list highlights problems with IOM's suggestion that one can interpret the sum of the regression coefficients on proxy occupation wages as a measure of the inclusion factor used in current GPCI policy. This sum directly corresponds to a transformed correlation coefficient physicians' relative regional wages and IOM's composite occupation wage index. Consequently, the "IOM inclusion factor" need not fall between zero and one as is the case with the inclusion factor under currently policy. The IOM inclusion factor can be negative; it can exceed one; and it can even equal zero. Such instances occur in the empirical findings reported here.

Evaluation of IOM Recommendations for the Office Rent Index

The PE GPCI office rent index currently relies on residential rental data to estimate physicians' costs for commercial office space. Using such rental data as a proxy for commercial rents is valid as long as residential rents are proportional to commercial rents across payment areas. While such circumstances can occur in flexible markets where people can use land for both residential and commercial purposes, markets can readily produce differential demands for residential and commercial properties due to such factors as zoning laws. Additionally, both demand and supply factors could cause geographic variation in residential rents to *not* be proportional to regional variation in commercial rents. Due to the limitations of using residential rent data, IOM proposes that a new source of data be developed to determine the variation in the price of commercial office rent per square foot.

IOM's proposal for identifying a source of commercial rent data to compute the office rent index offers a number of attractive features. Although collecting rent data from physicians could improve the accuracy of the office rent index, such an effort would encounter several challenges: (i) collecting a new source of office rent data would be administratively costly, (ii) physician response rates are typically low, (iii) utilizing office rent data collected directly from physicians would introduce a circularity problem, and (iv) developing and collecting a new source of commercial office rent might partially replicate existing data sources currently being studied. Our report identifies commercial rent data from the CoStar Group as a potential candidate to replace the residential rent data currently used by GPCI in its calculations. CoStar offers a detailed database that contains national commercial office rent data for over 2.8 million commercial properties covering over 10 billion square feet of space. The database also tracks a wide variety of property types and contains a relatively large number of commercial property listings for rural states. The disadvantages of using CoStar are that it is fairly expensive and—since the data source is proprietary—providers would not be able to fully validate the office rent index calculations. This report recommends that future research should examine the impact of using CoStar commercial rent data on the office rent index. Until these data are studied, however, in the short-term this report recommends the continued use of the large and nationally representative residential rent data available in the ACS.

Summary of Empirical Impact Analysis

To determine whether the IOM recommendations cause a meaningful change in physician GAF values in practice, this report conducts a series of impact analyses of the IOM recommendations. Table 6 presents these summary statistics. The first column lists the impact analyses carried out in this report. The second column specifies the number of counties or localities used to calculate GAF values. The third and fourth columns describe the median change and absolute mean change. The remaining four columns present the distribution of absolute GAF changes.

Table 6: Distribution of Changes in GAF for Impact Analyses

Proposed IOM Modification	Total Obs.	Median Change	Abs. Mean Change	Distribution of Absolute GAF Changes			
				0.00 to 0.01	0.01 to 0.05	0.05 to 0.10	> 0.10
Three-Tiered Payment Areas	3223 Counties	-0.025	0.028	14.2%	77.8%	7.3%	0.8%
Regression-Based PW GPCI (FP Specification)	89 Localities	0.007	0.029	24.8%	58.4%	16.8%	0%
Alternative Proxy Occ., Current PW GPCI Methodology	89 Localities	0.000	0.004	96.6%	3.3%	0%	0%

The two IOM policy recommendations that induce the largest changes in GAF values consist of modifying the definitions of GPCI payment area and using a regression-based approach to calculate the PW GPCI. In both cases, the average change in GAF values is around 3 percentage points. Since IOM's proposal only applies the out-commuting adjustment to the employee wage index, the changes in county GAF values under the three-tiered payment area are similar in magnitude to what occurs when redefining all GPCI component payment areas to MSAs. Using an alternative set of proxy occupations to calculate PW GPCI values under the current methodology leads to less than a half of a percentage point change in GAF values.

TABLE OF CONTENTS

Executive Summary i
1 Introduction 1
2 Geographic Adjustments of Physician Fee Schedule Under Current Policy 4
2.1 How GPCIs Affect Physician Payments 4
2.2 GPCIs' Six Component Indices 5
2.3 Current Policy for Calculating GPCIs 6
2.3.1 Physician Work GPCI Methodology 7
2.3.2 Practice Expense GPCI Methodology 9
2.3.3 Malpractice GPCI Methodology 11
2.3.4 Data Sources Used to Calculate GPCIs 11
2.3.5 Legislative Adjustments 12
3 Description of IOM's GPCI Recommendations 14
3.1 Recommended Changes to the Employee Wage Index 16
3.1.1 Redefining Labor Market Payment Areas 16
3.1.2 IOM Employee Wage Index: A Numerical Example 19
3.1.3 IOM's Three Smoothing Specifications 22
3.1.4 Wage Measurement Recommendations 23
3.2 Recommended Changes to Measurement of Physician Wages 24
3.3 Recommended Changes to Data Sources Used to Compute Office Rents 26
3.4 Endorsement of Current Purchased Services Index Methodology 27
3.5 Endorsement of Current GPCI Cost Share Weights 27
4 Evaluation of GPCI Employee Wage Recommendations 29
4.1 Characterization of IOM's Recommended Payment Areas for Labor Markets 29
4.1.1 Simple Depiction of Labor Markets for Physician Offices 30
4.1.2 Calculation of IOM Employee Wage Index in this Example 33
4.1.3 Issues with IOM's Commuting Shares 34
4.1.4 Illustrations of IOM's Out-Commuting Adjustment 34
4.2 Empirical Impacts of IOM's Commuting-Based Smoothing Approach 39
4.2.1 Out-Commuting Adjustment's Effect on the Presence of GAF Cliffs 40
4.2.2 Data Sources for Implementing IOM Commuting Adjustments 41
4.3 Measuring Wages of Workers in the Healthcare Industry 42
4.3.1 Advantages and Disadvantages of Using Industry-Specific Wage Data 42
4.3.2 Advantages and Disadvantages of Using Confidential BLS OES Data 45
5 Evaluation of Physician Work GPCI Recommendations 47
5.1 Discussion of Regression Approach for Predicting Physician Wages 47
5.2 Methods and Data Sources for Measuring Physician Wages 50
5.2.1 IOM Proposed Adjustments of Physician Earnings 50
5.2.2 Candidate Data Sources for Predicting Physician Wages 52
5.3 Empirical Findings Using IOM Regression Approach 56
5.3.1 Regression Specifications 57
5.3.2 Regression Results 60
5.4 Estimates Using Alternative Proxy Occupations 66
6 Evaluation of GPCI Office Rent Recommendations 69
6.1 Creating a New Data Source for Commercial Rents 69
6.2 Existing Commercial Rent Data Sources 70

6.2.1 CoStar Group ... 71
6.2.2 LoopNet ... 72
6.2.3 Reis, Inc. ... 72
6.2.4 Medical Group Management Association (MGMA) ... 72
6.2.5 Federal Agencies: USPS and GSA ... 73
6.2.6 Overview: Comparison of Commercial Rent Data Sources ... 73
6.3 Residential Rent Data Sources ... 75
6.3.1 American Community Survey ... 75
6.3.2 HUD Fair Market Rents ... 76
6.3.3 Basic Allowance for Housing ... 77
7 Empirical Impacts of IOM Recommendations ... 78
7.1 Effects of Redefining Payment Areas ... 78
7.1.1 Implementing the Out-Commuting Based Smoothing Adjustment ... 79
7.1.2 Payment Area Definitions Based on MSAs ... 81
7.1.3 Implementing IOM Three-Tiered Payment Area Recommendations ... 85
7.2 Effects of Regression-Based Methodology for Calculating PW GPCI ... 86
7.3 Effects Using an Alternative Set of PW GPCI Proxy Occupations ... 88
7.3.1 Impacts of Alternative Occupations Using Current Methodology ... 89
7.3.2 Impacts of Alternative Occupations Using Regression-Based Methodology ... 90
8 Summary of Findings ... 93
8.1 Evaluation of IOM's Employee Wage Recommendations ... 93
8.2 Evaluation of IOM's PW GPCI Recommendations ... 94
8.3 Evaluation of IOM's Office Rent Recommendations ... 96
8.4 Empirical Impacts of IOM Recommendations on GAF Values ... 96
References ... 98
Appendix A : Current Employee Wage Index Calculation ... 101
A.1 Selecting the occupations for inclusion in the wage index calculation ... 101
A.2 Calculating an RVU-weighted national average hourly wage by occupation ... 101
A.3 Indexing the occupation wage in each MSA to the national wage ... 102
A.4 Calculating occupations' share of the national employee wage expenditure ... 102
A.5 Calculating MSA-level hourly wage index ... 102
A.6 Calculating locality-level employee wage index ... 103
Appendix B : Impact of IOM's MSA-Based Payment Areas ... 104
B.1 Payment Areas Definitions ... 104
B.2 Measuring Variability Across Four Candidate Payment Areas ... 105
B.3 Measuring Variability Across Four Candidate Payment Areas ... 106
Appendix C : Unweighted PW GPCI Regression ... 110
Appendix D : Alternative Specification for the Proxy Occupations ... 112

LIST OF TABLES AND FIGURES

Table 1: Breakdown of GPCIs into Six Component Indices ii
Table 2: IOM Geographic Practice Cost Index (GPCI) Recommendations iii
Table 3: IOM's Suggested Three-Tiered System for Defining GPCI Payment Areas iv
Table 4: Example Application of the IOM Out-Commuting Adjustment v
Table 5: Summary of Changes to PW GPCI Components viii
Table 6: Distribution of Changes in GAF for Impact Analyses x
Table 2.1: Breakdown of GPCIs into Six Component Indices 6
Table 2.2 Wage Bill Shares for Fifth and Sixth Updates 8
Table 2.3: Data Sources Used for Recent GPCI Updates 12
Table 3.1: IOM GPCI Recommendations 14
Table 3.2 IOM's Suggested Three-Tiered System for Defining GPCI Payment Areas 15
Table 3.3: Illustrating Step 1 of the IOM Employee Wage Index Calculation 20
Table 3.4: Illustrating Step 2 of the IOM Employee Wage Index Calculation 21
Table 3.5: Application of Smoothing Adjustments under Three IOM Outmigration Models 22
Table 3.6: Summary of Changes to PW GPCI Components 24
Figure 4.1: Illustration of Local Labor Markets for Three Physician Offices 31
Table 4.1: Commuting Shares and Wages, Urban-Rural Example 35
Table 4.2: Calculation of the IOM EWI, Urban-Rural Example 36
Figure 4.2: Illustration of Local Labor Markets with Commuting Barrier 38
Table 4.3: Commuting Shares and Wages, Commuting-Barrier Example 38
Table 4.4: Counterintuitive Implication of IOM Smoothing, Commuting-Barrier Example 38
Figure 4.3: Difference in County GAF Values with Out-Commuting Adjustment 41
Table 4.5: Example of Cross-Industry Wage Variability for Registered Nurses 44
Table 4.6: Nursing Wages by Industry (BLS OES 2010) 44
Table 4.7: Concentration of Physicians' Workers in Healthcare Industry (BLS OES 2010) 45
Table 5.1: Proposed Adjustments for Physician Earnings Data 51
Table 5.2: Data Available to Measure Physician Earnings 53
Table 5.3: Method of Physician Compensation by Specialty (2011 MGMA Data) 54
Table 5.4: Regression Results for PW GPCI Using Current Proxy Occupations 61
Table 5.5: Family and General Practitioner Wages by Rural-Urban Status (BLS OES 2008) 63
Table 5.6: Regression Results for PW GPCI Using 2005-2009 ACS 65
Table 5.7: Regression Results for PW GPCI Using Alternative Occupations 68
Table 5.8: Comparison of PW GPCI Regressions Using Original and Alternative Occupations 68
Table 6.1: Comparison of Data Sources for Office Rent 74
Table 7.1: Summary of IOM's Payment Area Recommendations 79
Table 7.2: Difference in Employee Wage Index With and Without Smoothing 80
Table 7.3: Difference in PE GPCI With and Without Smoothing 81
Table 7.4: Difference in GAF With vs. Without Smoothing 81
Table 7.5: Difference in GAF when Switching to MSAs (Locality Baseline) 83
Table 7.6: Difference in GAF when Switching to Counties (Locality Baseline) 83
Table 7.7: Difference in GAF when Switching to Statewide Tiers (Locality Baseline) 83
Table 7.8: Change in GAF by Urban-Rural Continuum Code 85
Table 7.9: Difference in GAF: IOM Three-Tiered Payment Area vs. Medicare Locality 86
Table 7.10: Impact Analysis: Specialty-Mix Regression (PW GPCI) 87
Table 7.11: Impact Analysis: Specialty-Mix Regression (GAF) 87

Table 7.12: Impact Analysis: Family Practice Regression (PW GPCI) 88
Table 7.13: Impact Analysis: Family Practice Regression (GAF) 88
Table 7.14: Alternative Proxy Occupations Impact Analysis (PW GPCI)................................... 89
Table 7.15: Alternative Proxy Occupations Impact Analysis (GAF)... 90
Table 7.16: Alternative Occupation Impact Analysis: Specialty-Mix Regression (PW GPCI) ... 91
Table 7.17: Alternative Occupation Impact Analysis: Specialty-Mix Regression (GAF) 91
Table 7.18: Alternative Occupation Impact Analysis: FP Regression (PW GPCI)...................... 91
Table 7.19: Alternative Occupation Impact Analysis: FP Regression (GAF)............................... 92
Table B.1: Summary of GAF Values by Alternate Payment Areas 106
Figure B.1: Difference in County GAF Values in Different Localities by Distance.................. 108
Figure B.2: Share of Counties with GAF Differential Greater Than 0.05 by Distance............. 109
Table C.1: Weighted vs. Unweighted PW GPCI Regressions (Original Occupations)............. 110
Table C.2: Weighted vs. Unweighted PW GPCI Regressions (Alternate Occupations)............ 111
Table D.1: Summary Statistics for Alternative PW GPCI Proxy Occupations 112
Table D.2: Regression Results for PW GPCI Using Alternative Occupations........................... 114

LIST OF ABBREVIATIONS

ACA: Affordable Care Act
ACO: Accountable Care Organization
ACS: American Community Survey
ACS PUMS: American Community Survey Public Use Micro Sample
AMA: American Medical Association
AMA PPIS: American Medical Association Physician Practices Information Survey
BLS: Bureau of Labor Statistics
BOMA: Building Owners and Managers Association
CF: Conversion Factor
CMS: Centers for Medicare and Medicaid Services
CPI: Consumer Price Index
CTPP: Census Transportation Planning Package
CTS: Community Tracking Survey
CWA: Census Work Area
CY: Calendar Year
DOD: United States Department of Defense
DOD BAH: U.S. Department of Defense Basic Allowance for Housing
ECI: Employment Cost Index
EWI: Employee Wage Index
FMR: US Department of Housing and Urban Development's Fair Market Rent data
FDIC: Federal Deposit Insurance Corporation
FS: Full Service
FY: Fiscal Year
GAF: Geographic Adjustment Factor
GAO: Government Accountability Office
GPCI: Geographic Practice Cost Index
GSA: General Services Administration
HCPCS: Healthcare Common Procedure Coding System
HSPA: Health Professional Shortage Areas
HUD: United States Department of Housing and Urban Development
HWI: Hospital Wage Index
IOM: Institute of Medicine
IPPS: Inpatient Prospective Payment System
LPN: Licensed Practical Nurse
MEI: Medicare Economic Index
MG: Modified Gross
MGMA: Medical Group Management Association
MHA: Military Housing Area
MHW: Mean/Median Hourly Wage
MP: Malpractice
MSA: Metropolitan Statistical Area
OACT: Office of the Actuary
OB/GYN: Obstetrician/Gynecologist
OES: Occupational Employment Statistics
PE: Practice Expense
PFS: Physician Fee Schedule
PW: Physician Work
RBRVS: Resource-Based Relative Value Scale
RN: Registered Nurse
RVU: Relative Value Unit
SGR: Sustainable Growth Rate
USDA: United States Department of Agriculture
USPS: United States Postal Service

1 INTRODUCTION

Medicare pays physicians for their services according to the Physician Fee Schedule (PFS), which specifies a set of allowable procedures and payments for each service. Each procedure is interpreted as being produced by a combination of three categories of inputs: physician work (PW), practice expense (PE), and malpractice insurance (MP). The particular blend of PW, PE, and MP inputs assessed to produce a service specifies its composition of relative value units (RVUs). A payment for a procedure depends on its assigned RVUs and the input prices assessed for each RVU component. Under mandates in Section 1848(e) of the Social Security Act, the Centers for Medicare and Medicaid Services (CMS) must apply geographic cost indices in the calculation of component RVU input prices. Starting in 1992, CMS introduced Geographic Practice Cost Indices (GPCIs) to comply with this mandate; CMS updates GPCIs at least every three years.

Concerns have been expressed regarding the accuracy of GPCIs in measuring physicians' regional cost differences. In a 2005 report, the Government Accountability Office (GAO) stated that the "geographic adjustment indices are valid in design," but questioned the applicability of the wage and rental data used to calculate PE GPCIs.[1] GAO recommended augmenting wage data to cover a wider array of occupations and basing rents on commercial office rents instead of residential rents which GPCIs currently rely upon. GAO also advised CMS to refine malpractice GPCIs by standardizing input data collection and making them more complete and representative. In addition to changes in the wage, rent, and malpractice premium data CMS uses, GAO further raised issues about how to measure physician wages when some physicians are self-employed and other are salaried, as well as what area is applicable for defining physician wage indices. GAO, along with other critics, have questioned the appropriate constructions of localities for calculating all forms of GPCIs; GAO found that substantial variation in practice costs existed within each payment area under the current locality-based system.

In its latest efforts to improve the methodology and data sources used to compute GPCIs and other geographic input cost adjustments, CMS sponsored the Institute of Medicine (IOM) to produce a series of reports examining how CMS measures geographic variation in input prices faced by physicians.[2] In its Phase I report published in September 2011, IOM's "Committee on Geographic Adjustment Factors in Medicare Payment" evaluates the accuracy of the current geographic adjustment factors, the methodology used to make adjustments, and the extent to which alternative sources of data are representative of relevant circumstances for healthcare providers. The IOM report offers a range of recommended modifications to the methodology

[1] U.S. GAO March 2005.

[2] In addition to GPCIs, IOM was also asked to evaluate the Hospital Wage Index (HWI) methodology used by CMS to adjust payments to hospitals and other institutional providers.

and data used to compute the hospital wage index (HWI) and GPCIs.[3] Regarding GPCIs, some of IOM's recommendations support CMS's current practices (e.g., continued use of the MEI cost share weights) and others that CMS has already adopted for calendar year (CY) 2012 (e.g., creation of the purchased service index).

The new changes to the GPCI calculations recommended by IOM fall principally into three categories of modifications in methodologies and data:

(1) Compute the employee wage components of the PE GPCI using counties as payment areas with wages adjusted for commuting patterns and using data on healthcare workers;
(2) Use a regression-based approach to measure regional variation in physician wages in the PW GPCI; and
(3) Identify a source of commercial office rent data to measure regional variation in physicians' cost to rent office space as part of the PE GPCI.

IOM recommendation (1) argues for redefining payment areas for employee wage indices as the county in which a physician office is located with wages measured to account for workers' commuting patterns across metropolitan statistical areas (MSAs) and with wage data on workers from firms in the healthcare industry (rather than from all industries) recognizing occupational mixes consistent with workforces in physician offices. This revision of the PE GPCI wage component would align it with IOM's recommendations regarding calculation of wage indices for hospitals and other institutional providers. IOM recommendation (2) would replace CMS's current PW GPCI values, which are equal to a weighted average of proxy-occupation wage index values, with a regression framework to compute regional differentials in physician wages. Finally, IOM recommendation (3) suggest replacing the residential rent data currently used to measure regional variation in office rents with a new source of office rent data.

The discussion in the sections below evaluates the potential impacts of implementing the IOM recommendations from both conceptual and empirical perspectives. The conceptual analysis weighs the advantages and disadvantages of each of the three IOM recommendations categories listed above. Additional work evaluates alternative methods for formulating payment areas and labor markets across multiple GPCI component indices. The empirical analysis investigates whether the identified conceptual challenges become problematic in practice, and it further explores the impacts of the IOM recommendations on the values of GPCI indices.

The remainder of this report consists of seven sections. Section 2 provides an overview of the Resource-Based Relative Value Scale (RBRVS) system and describes how CMS currently uses GPCIs to adjust physician payments. Section 3 explains IOM's recommended changes to

[3] IOM 2011.

the GPCI methodology. Sections 4, 5, and 6 evaluate each of the three IOM recommendation categories described above in detail. Specifically, Section 4 examines issues related to measuring regional variation in employee wages, Section 5 evaluates IOM's proposals to redefine the methodology used to measure regional variation in physician wages, and Section 6 assess potential sources of office rent data that CMS could use to calculate the office rent index. Section 7 presents an empirical analysis showing the prospective impacts of adopting IOM recommendation on the values of GPCIs. Finally, Section 8 concludes with a summary of findings.

2 GEOGRAPHIC ADJUSTMENTS OF PHYSICIAN FEE SCHEDULE UNDER CURRENT POLICY

Where physicians locate their practices affects their cost of providing each service. For instance, the cost of living for physicians is higher in Manhattan than in Montana; the cost of operating a physician practice is higher in San Francisco than in Sandusky, Ohio; and purchasing malpractice insurance is more expensive for a physician in Miami than for one in Minneapolis. To account for these geographic differences in input costs, CMS modifies the payments it makes to physicians using GPCIs. GPCIs adjust physician payments based on geographic differences in physician wages, practice expenses, and the price of malpractice insurance. In fact, CMS creates three GPCIs—PW, PE, and MP—which correspond to the three broad classes of inputs physician practices use.

The remainder of this section provides additional background information regarding how CMS uses GPCIs within the Medicare PFS. Specifically, this section answers three questions:

- How do GPCIs affect Medicare payments to physicians?
- What are the six component indices that make up GPCIs?
- What methodology does CMS currently use to calculate GPCIs?

The following three sections answer each of these questions in the order they appear above.

2.1 How GPCIs Affect Physician Payments

Under the PFS, Medicare pays for physician services based on a list of services and their payment rates. Under the PFS, every physician service corresponds to a specific procedure code within the Healthcare Common Procedure Coding System (HCPCS). Since 1992, CMS has relied on the RBRVS system to determine the fee for each procedure. In the RBRVS system, payments for each service depend on the relative amounts of inputs required to perform the procedure. These inputs include the amount of physician work needed to provide a medical service, expenses related to maintaining a practice, and malpractice insurance costs. CMS estimates the quantity of inputs required to provide these services using PW, PE, and MP RVUs, respectively.

The three GPCIs adjust their corresponding RVUs for regional variation in the price of each of the three input categories. GPCIs increase the RVU values for high-cost areas and reduce the RVU values for low-cost areas. GPCIs do not affect aggregate payment levels; instead, they reallocate payment rates by locality to reflect regional variation in relative input prices. For instance, a PE GPCI of 1.2 indicates that practices expenses in that area are 20 percent above the national average, whereas a PE GPCI of 0.8 indicates that practices expenses in that area are 20 percent below the national average.

CMS calculates the three GPCIs for 89 payment areas known as Medicare localities. Each physician payment locality is assigned an index value, which equals input cost estimates within each payment area over the average input cost at the national level. Localities are defined alternatively by state boundaries (e.g., Wisconsin), MSAs (e.g., Metropolitan St. Louis, MO), portions of an MSA (e.g., Manhattan), or rest-of-state area which exclude metropolitan areas (e.g., Rest of Missouri).[4] As a result, some localities are large metropolitan areas, such as San Francisco and Boston, whereas many are statewide payment areas that include both metropolitan and nonmetropolitan areas, such as Minnesota, Ohio, and Virginia.[5]

Using the RVUs, GPCIs, and a conversion factor (CF), one can calculate the physician payment for any service in any locality. The CF translates the sum of the GPCI-adjusted RVUs into a payment amount. Equation (2.1) below demonstrates how the PW, PE, and MP GPCIs combine with the three RVUs and the CF to establish a Medicare physician payment for any service *H* in locality *L*:[6]

(2.1) $$Payment_{H,L} = [\underbrace{(GPCI_{PW,L} \times RVU_{PW,H})}_{\boxed{\text{Physician Work}}} + \underbrace{(GPCI_{PE,L} \times RVU_{PE,H})}_{\boxed{\text{Practice Expense}}} + \underbrace{(GPCI_{MP,L} \times RVU_{MP,H})}_{\boxed{\text{Malpractice Insurance}}}] \times CF$$

Although GPCIs affect payments for each procedure depending on the relative amounts of PW, PE, and MP RVUs, one can summarize the combined impact of the three GPCI components on a locality's physician reimbursement levels using the Geographic Adjustment Factor (GAF). The GAF is a weighted average of the three GPCIs for each locality, where the weights are determined by the Medicare Economic Index (MEI) base year weights. Using the 2006 MEI base weights, one can calculate the GAF as follows:

(2.2) $$GAF_L = (GPCI_{PW,L} \times 0.48266) + (GPCI_{PE,L} \times 0.47439) + (GPCI_{MP,L} \times 0.04295).$$

2.2 GPCIs' Six Component Indices

CMS uses six component indices to calculate the three GPCIs. Table 2.1 maps the corresponding component index to its relevant GPCI. Whereas the PW and MP GPCIs are comprised of a single index, the PE GPCI is comprised of four component indices (i.e., the employee wage; purchased services; office rent; and equipment, supplies and other indices). The first component of the PE GPCI, the employee wage index, measures regional variation in the cost of hiring skilled and unskilled labor directly employed by the practice. Practice expenses

[4] An MSA is comprised of one or more counties and includes the counties that contain a core urban area with a population of 50,000 or more, as well as surrounding counties that exhibit a high degree of social and economic integration. For more information, see the U.S. Census Bureau website: http://www.census.gov/population/metro/.
[5] For a brief history of the changes to GPCI payment areas from their inception in 1966 to the current regulation, see: U.S. GAO June 2007 and CMS 1993.
[6] The Medicare physician payment calculated using equation (2.1) may also be adjusted upwards or downwards through payment modifiers. For example, physicians use a modifier to bill for a service when they assist in a surgery; payment for an assistant surgeon is only a percentage of the fee schedule amount for the primary surgeon.

for employee wages account for the largest share of the PE GPCI. Although the employee wage index adjusts for regional variation in the cost of labor employed directly by physician practices, the employee wage index does not account for geographic variation of practices' costs for services that have been outsourced to other firms. Such cases occur when practices purchase services from law firms, accounting firms, information technology consultants, building service managers, or any other third-party vendor. The second component, the purchased services index, measures regional variation in the cost of these contracted services that physicians typically buy. The third component, the office rent index, measures regional variation in the cost of typical physician office rents. For example, renting an office in San Francisco is more expensive than renting an office in Wyoming; the office rent index produces an estimate of this regional variation in the price of office space. Finally, the "equipment, supplies and other" category measures practice expenses associated with a wide range of costs from chemicals and rubber, to telephone and postage. CMS assumes that these capital goods are purchased in a national market and does not adjust for regional variation in practice costs within the "equipment, supplies and other" category; thus, each locality receives a value of one for the "equipment, supplies and other" index.

Table 2.1: Breakdown of GPCIs into Six Component Indices

GPCI	Component Index	Measures Geographic Differences in:
Physician Work	Single Component	Physician wages
Practice Expense	*Employee Wage*	Wages of clinical and administrative office staff
	Purchased Services	Cost of contracted services (e.g., accounting, legal, advertising, consulting, landscaping)
	Office Rent	Physician cost to rent office space
	Equipment, Supplies, and Other	Practice expenses for inputs such as chemicals and rubber, telephone use and postage
Malpractice	Single Component	Cost of professional liability insurance

2.3 Current Policy for Calculating GPCIs

Calculating GPCI values requires measuring the price of each input relative to its national average price. Although the general approach is similar across all geographically-adjusted component indices, the specific methodology and data used to calculate each index value vary. For instance, whereas the employee wage index measures worker wages directly, the PW GPCI measures regional variation in physician wages using proxy occupations; whereas labor-related indices rely on wage data from the Bureau of Labor Statistics (BLS) Occupational Employment

Statistics (OES); the office rent index uses the American Community Survey (ACS) to measure regional variation in office rents.

The remainder of this section describes the methodology for calculating the six GPCI component indices. Sections 2.3.1, 2.3.2 and 2.3.3 contain an overview of the methodology for calculating the component indices within the PW GPCI, PE GPCI, and MP GPCI, respectively. Section 2.3.4 describes the data CMS currently uses to calculate each GPCI component. Section 2.3.5 presents some of the legislative adjustments that affect GPCI values but which are not discussed in the general GPCI methodology. A more detailed description of the methodology used to calculate the GPCI component indices can be found in previous reports describing the Sixth Update[7] and Revisions to the Sixth Update.[8]

2.3.1 Physician Work GPCI Methodology

In the current methodology, CMS defines PW GPCI values based on regional variation in wages across a set of proxy occupations. Although direct measures of physician wages are available in nationally representative data sources (e.g., BLS OES, ACS), CMS elects not to use this information in its PW GPCI calculation. According to a 2005 GAO report, computing the PW GPCI using direct measures of physician wages would produce a circular measure where the work adjustment would depend on past payments to physicians by Medicare; to attenuate this problem, CMS uses proxy occupation wages in its calculation of PW GPCI values. Specifically, CMS uses the following four steps to calculate the PW GPCI:

(1) Select proxy occupations and calculate an occupation-specific index for each proxy;
(2) Assign weights to each proxy-occupation index to create an aggregate proxy-occupation index at the locality level;
(3) Adjust the aggregate proxy-occupation index by a physician inclusion factor; and
(4) Re-scale the PW GPCI to ensure budget neutrality.

The proxy occupations Medicare currently selects in the first step represent highly educated, professional occupation categories, whose wages would be expected to reflect the overall geographic differences in living costs and amenities for other professional workers. To develop a labor cost index for the physician's own work, the current PW GPCI draws on the regional variation in the earnings of the following professionals:

- Architecture and Engineering,
- Computer, Mathematical, Life and Physical Science,
- Social Science, Community and Social Service, and Legal,
- Education, Training, and Library,

[7] O'Brien-Strain, et al. November 2010.
[8] MaCurdy, et al. October 2011.

- Registered Nurses,
- Pharmacists, and
- Art, Design, Entertainment, Sports, and Media.

Using BLS OES data, CMS calculates an occupation-specific index for each of the proxy groups. The occupation-specific index in a given county is the median hourly earnings for that occupation relative to RVU-weighted national average median hourly earnings. As BLS OES wage data are reported by MSA, all counties in the same MSA receive the same proxy occupation index value.

To create an aggregate proxy-occupation index, the second step weights these occupation-specific indices by each occupational group's share of the national wage bill. An occupation's share of the national wage bill equals the national hourly wage for that occupation multiplied by the number of non-zero wage earners in that occupation nationally and then divided by the wage bill summed across all proxy occupations. Table 2.2 lists the wage bill shares utilized in the Fifth and Sixth Updates for the seven occupation groups.

Table 2.2 Wage Bill Shares for Fifth and Sixth Updates

Occupation Group	Fifth Update	Sixth Update
Architecture and Engineering	13.9%	8.5%
Computer, mathematical, life and physical science	19.1%	16.0%
Social science, community & social service, and legal	15.5%	8.5%
Education, training, and library	30.6%	40.2%
Registered nurses	11.1%	16.6%
Pharmacists	1.6%	2.8%
Art, design, entertainment, sports, and media.	8.2%	7.4%
Total	100%	100%

Using the wage bill share, one can calculate the county-specific hourly index as the sum of the product of the county indices for each occupation times the wage bill share for each occupation. The preliminary county-level physician wage index is then aggregated to the locality level by weighting the county indices described above by the number of PW RVUs in each county. Then, one can translate the county-level PW GPCI index to a locality-level index using the following formula:

$$X_L = \frac{\sum_{k \in \{k_L\}} RVU_{PE,k} \times X_k}{\sum_{k \in \{k_L\}} RVU_{PE,k}} \qquad (2.3)$$

where X_L is the locality-level index composite index, X_k is the county-level index, and $RVU_{PE,k}$ is the number or PE RVUs that were billed in each county. The expression $k \in \{k_L\}$ indicates the summation over all counties that are located in locality L.

The third step implements the Congressionally-mandated PW GPCI inclusion factor. The inclusion factor reduces the magnitude of the variability in the PW GPCI. After applying the physician inclusion factor, the adjusted PW GPCI can be calculated as:

$$GPCI_{PW,L} = 1 + (Inclusion\ Factor) \times (X_L - 1) \tag{2.4}$$

where the left hand side variable is the PW GPCI for locality L, and X_L is the locality proxy estimated in the second step above. An inclusion factor of one (i.e., 100 percent) would account for all observable variation in physician wages, and the PW GPCI would equal the locality proxy X_L; an inclusion factor of zero (i.e., 0 percent) would remove geographic adjustments and would set the PW GPCI to one in all areas. As mandated by section 1848(e)(1)(A)(iii) of the Social Security Act, the current inclusion factor is 25 percent. If the locality proxy was 1.4, for example, after applying the 25 percent inclusion factor the PW GPCI would equal 1.1. Reducing the inclusion factor aims to equalize physician compensation across areas.[9]

The fourth and final step rescales the PW GPCI to ensure budget neutrality. Budget neutrality adjustments are applied in the final step of calculating each GPCI to ensure that the total payments distributed remain the same under the updated PW GPCIs as they were under the previous PW GPCIs.

2.3.2 Practice Expense GPCI Methodology

Although the approach for calculating each of the four PE GPCI component indices differs, all geographically-adjusted indices broadly follow the same three steps. To present the general framework for calculating the PE GPCI indices, this section begins by describing the approach for the office rent index, which uses the following steps:

(1) Calculate an RVU-weighted national average rent value using county rent data;
(2) Create a county-specific index; and
(3) Calculate a Medicare locality-level index.

The office rent index currently measures regional variation in the price of office rents using residential rent data from the ACS on median gross rents for two-bedroom apartments. In step 1, one calculates national average rents as follows:

$$R_N = \frac{\sum_k RVU_{PE,k} \times R_k}{\sum_k RVU_{PE,k}} \tag{2.5}$$

where R_N is the RVU-weighted national average, $RVU_{PE,k}$ is the number of PE RVUs in county k, and R_k is the median gross rent in county k. Using the national rent estimate, one can create a county-specific rent index in step 2 as the ratio of the county gross rents and the national average rents as follows:

[9] Zuckerman et al. September 2004.

(2.6)
$$X_k = \frac{R_k}{R_N}$$

In this case, X_k is the office rent index for county k. In step 3, one aggregates the county-level office rent index to locality-level office rent index as shown in equation (2.3).

Although the employee wage index relies on a similar approach, CMS relies on wage data across multiple occupations to create a composite index describing regional variation in the wages of workers typically employed by physician practices. To compute a composite index for any county, one follows the same steps used to compute the PW GPCI with the exception that no inclusion factor is applied (or, equivalently, the inclusion factor is 100%). When translating this approach to the employee wage index case, step 1 creates a county-level index for each occupation employed in the offices of physician industry, where the county-level occupation specific index equals the occupation's median wage in the county divided by the RVU-weighted national average wage for that occupation. Unlike the PW GPCI, the employee wage index directly measures the wages of workers employed by physicians and does not use proxy occupations. Step 2 calculates a composite wage index for each county as a weighted average of these occupation-specific indices. The weights in this weighted average equal each occupation's share of the national wage bill within the offices of physicians industry. Once CMS calculates the composite wage for each county, one aggregates the county-level index to the locality level as described in equation (2.3).

The methodology for computing the purchased services index follows the same broad approach with three modifications. First, rather than including occupations that are employed in physician offices, the purchased services index includes occupations employed in industries from which physicians are likely to purchase services. Second, the weight each occupation receives in the composite index differs between the employee wage index and purchased services index. Whereas the employee wage index weights each occupation based on each share of the national wage bill in the offices of physician industry, the purchased services index weights occupations based on their national wage share within the industries from which physicians purchase services. Third, unlike the employee wage index, only a portion of the purchased services index is geographically adjusted. Because capital expenses make up approximately 38 percent of purchased services inputs, only 62 percent of the index is adjusted for regional variation in labor costs.[10]

The only PE GPCI component that does not follow the general methodology presented above is the "equipment, supplies and other" index. This index is not geographically adjusted. Thus, all localities receive an equipment and supplies component index value of 1.0.

[10] The exact proportion of the occupation-specific index that is regionally adjusted depends on the labor-related share of expenses in the industries in which that occupation is most frequently employed.

2.3.3 Malpractice GPCI Methodology

MP GPCI largely follows the general PE GPCI methodology but has three unique features. First, like the employee wage index, the MP GPCI is a composite index; whereas the employee wage index is a composite of median wages for specific occupations, however, the malpractice GPCI is a composite index that combines measures of regional variation in malpractice premiums across physician specialties. To create the specialty-mix adjusted composite index, one calculates a county-specific index based on the premium levels for each specialty, and then one calculates the composite county-index as a weighted average of these specialty-specific malpractice indices. Second, whereas all PE GPCI component indices use national weights when creating a composite index, the malpractice GPCI relies on state-specific specialty weights. This specification reflects the fact that state malpractice premiums by specialty in part reflect the norms of care in each state. Third, whereas most other component indices use ACS or BLS data to create their index values, CMS principally uses malpractice premium state rate filing data.[11]

2.3.4 Data Sources Used to Calculate GPCIs

CMS relies on a number of data sources to calculate the GPCI components. Table 2.3 compares the data sources used under the 2012 Sixth Update and the Revisions to the Sixth Update implemented in CY 2012. Of particular importance are the BLS OES establishment data and the ACS household data. CMS uses the former to measure regional variation in the cost of labor-related inputs and the latter to measure regional variation in rents.

The BLS OES survey is a semi-annual mail survey of all salaried non-farm workers, excluding self-employed individuals, administered by the BLS. OES data from any year are aggregated using six semi-annual panels collected over three years.[12] The 2008 OES wage estimates, for example, contain employer survey responses from May 2008, November 2007, May 2007, November 2006, May 2006, and November 2005. The establishments surveyed are selected from lists maintained by State Workforce Agencies for unemployment insurance purposes. To create a sample for the OES data, BLS selects establishments from every metropolitan area and state, across all surveyed industries, and from establishments of varying sizes. The OES program produces employment and wage estimates for over 800 occupations across 23 major occupational groups, including "healthcare practitioners" and "healthcare

[11] For a detailed description of the malpractice premium data used for the MP GPCI, see O'Brien Strain et al. November 2010.

[12] The BLS OES uses data over time to increase the sample size of the survey, thereby increasing reliability and reducing sampling error. But labor costs change over time, as evidenced by the Employment Cost Index (ECI) time series data. To make the data from all survey respondents comparable, the OES program uses the ECI to translate the occupation-level wages from previous years into a wage number for the most recent year. For additional details, see the BLS OES Technical Notes: http://www.bls.gov/oes/current/oes_tec.htm.

support occupations." Using this sample of establishments, the BLS collects detailed wage data by industry, occupation, and region. For instance, the BLS OES data contain industry wage information for the healthcare sector and the offices of physicians industry.

Table 2.3: Data Sources Used for Recent GPCI Updates

Component	Sixth Update 2012	Revisions to the Sixth Update 2012 (Current Regulation)
Physician Work GPCI	2006-2008 BLS Occupational Employment Statistics	2006-2008 BLS Occupational Employment Statistics
Practice Expense GPCI		
Employee Wage	2006-2008 BLS Occupational Employment Statistics	2006-2008 BLS Occupational Employment Statistics
Office Rent	FY2010 HUD 50th Percentile Rents	2006-2008 American Community Survey
Purchased Services (Labor Cost)	*N/A*	2006-2008 BLS Occupational Employment Statistics
Purchased Services (Labor Related Shares)	*N/A*	CMS Labor-Related Classification
Equipment, Supplies, Other	1.000 for all counties	1.000 for all counties
Malpractice GPCI	2006-2007 Malpractice Premiums	2006-2007 Malpractice Premiums
Cost Share Weights	2000 MEI weights	2006 MEI weights
County RVU Weights	2008 RVUs	2009 RVUs

To estimate prevailing rental costs, CMS uses 2-bedroom rental data from the 2006-2008 American Community Survey. The ACS is an annual household survey conducted by the U.S. Census Bureau. The ACS samples nearly 3 million addresses each year, resulting in nearly 2 million final interviews, and replaces the decennial census long form.[13] To calculate the office rent index, CMS relies on a customized extract of the ACS data to measure average gross rents for each county.[14] For counties with fewer than 20,000 individuals, however, ACS does not publicly release rental rate data.

2.3.5 Legislative Adjustments

CMS implements a number of required adjustments after completing the core GPCI calculations. Section 1848(e)(1)(E) of the Act provides for a 1.0 floor for the PW GPCI, which was set to expire at the end of 2011, until it was extended through the end of CY 2012 by the Temporary Payroll Tax Cut Continuation Act of 2011 and the Middle Class Tax Relief and Job Creation Act of 2012. In addition, Section 1848(e)(1)(G) of the Social Security Act sets a

[13] U.S. Census Bureau November 2008.
[14] Utilities cannot be analyzed separately since some individuals' monthly rent covers the cost of utilities. Thus the 2006-2008 ACS data can only accurately measure gross rents (i.e., including utilities) rather than net rents.

permanent 1.5 PW GPCI floor for services furnished in Alaska beginning January 1, 2009. Further, section 1848(e)(1)(I) establishes a 1.0 PE GPCI floor for physicians' services furnished in frontier States effective January 1, 2011. The following states are considered to be "Frontier States" for CY 2013: Montana, North Dakota, Nevada, South Dakota, and Wyoming. The empirical analyses in this report, however, detail only the calculations of GPCIs *before final adjustments*.

3 DESCRIPTION OF IOM'S GPCI RECOMMENDATIONS

IOM recommended alterations of GPCIs fall into five broad categories. Table 3.1 maps each of IOM's recommendations to the associated category and provides a brief description of each recommendation. The first category includes IOM proposals related to calculation of the employee wage components of the PE GPCI, which suggest using counties as payment areas with wages adjusted for commuting patterns and using data on healthcare workers. The second category involves replacing CMS's current use of a weighted average of proxy-occupation wages by a regression framework to compute regional differentials in the physician wage component of GPCI. The third category includes recommended improvements in the source of office rent data that CMS uses to measure regional variation in physicians' cost to rent office space. The fourth and fifth categories comprise IOM recommendations that largely mirror modifications already incorporated in the Revision to the Sixth Update of the GPCI; in particular, the creation of the purchased service index has been implemented for the FY 2012 GPCIs, and GPCI calculations continue to use MEI cost share weights which was recently adopted in previous years.

Table 3.1: IOM GPCI Recommendations

Category	Number	Description
Employee Wages	2-1	The same labor market definition should be used for both the hospital wage index and the physician geographic adjustment factor. Metropolitan statistical areas and statewide non-metropolitan statistical areas should serve as the basis for defining these labor markets.
	2-2	The data used to construct the hospital wage index and the physician geographic adjustment factor should come from all healthcare employers.
	4-1	Wage indexes should be adjusted using formulas based on commuting patterns for healthcare workers who reside in a county located in one labor market but commute to work in a county located in another labor market.
	5-4	The practice expense GPCI should be constructed with the range of occupations employed in physicians' offices, each with a fixed national weight based on the hours of each occupation employed in physicians' offices nationwide.
	5-5	The Centers for Medicare and Medicaid Services and the Bureau of Labor Statistics should develop a data use agreement allowing the Bureau of Labor Statistics to analyze confidential BLS data for the Centers for Medicare and Medicaid Services.
Physician Wages	5-2	Proxies should continue to be used to measure geographic variation in the physician work adjustment, but CMS should determine whether the seven proxies currently in use should be modified.
	5-3	CMS should consider an alternative method for setting the percentage of the work adjustment based on a systematic empirical process.
Office Rent	5-6	A new source of data should be developed to determine the variation in the price of commercial office rent per square foot.
Purchased Services	5-7	Nonclinical labor-related expenses currently included under PE office expenses should be geographically adjusted as part of the wage component of the PE.
Cost Share Weights	5-1	GPCI cost share weights for adjusting fee-for-service payments to practitioners should continue to be national, including the three GPCIs (work, practice expense, and liability insurance) and the categories within the practice expense (office rent and personnel).

Although not to become a part of IOM's formal recommendations until its Phase II report, a theme guiding recommendations throughout IOM's Phase I report concerns development of a three-tiered system for defining payment areas: the first tier consists of counties to be used as the basis for calculating employee wage indices, with adjustments incorporated to account for workers' commuting patterns across MSAs; the second tier comprises MSA-based areas to be used for the geographic cost adjustments of the PW GPCI, MP GPCI, as well as PE GPCI components such as office rents and purchased services;[15] and the third tier consists of a national payment area for the PE GPCI component index for "Equipment, Supplies and Other." Table 3.2 presents an overview of IOM's suggested replacements of current GPCI localities by payment areas tailored to capture the market environments appropriate for determining payment of individual GPCI components. The rows of this table list the six individual GPCI components incorporated in the PFS and the columns list the regions entertained as candidates for calculating geographic adjustments of payments to physicians. In the fourth column, the statewide tier payment area—a candidate payment area presented in the July 2007 proposed rule as "Option 3"—combines counties into tiers within each state based on each county's relative GAF value.[16] An "*X*" in a row indicates the payment area tier suggested by IOM to compute the GPCI component indicated in the corresponding row. The table clearly shows that IOM favors MSAs as the principal choice for payment areas, with counties playing a role for employee wage indices and a national market for equipment and supplies. The empirical analysis in later sections assesses the impacts of considering each of the payment area candidates listed in Table 3.2, with the goal of placing the IOM recommendations in useful context.

Table 3.2 IOM's Suggested Three-Tiered System for Defining GPCI Payment Areas

GPCI Expense Category	**Payment Area**				
	County	***MSA***	***Statewide Tier***	***Locality***	***National***
Physician Work		**X**			
Practice Expense					
Employee Wage	**X**				
Purchased Services		**X**			
Office Rent		**X**			
Equipment, Supplies, Other					**X**
Malpractice Insurance		**X**			

[15] On pages 2-19 of their report, IOM "propose[s] a set of areas that are consistent with hospital markets, increasing the number of physician payment areas from the current 89 to 441 (the number of hospital payment areas)." The 441 areas refer to MSA and rest-of-state non-MSA areas.
[16] Appendix B contains a more detailed definition of statewide tiers.

Sections 3.1 through 3.5 fully explain each of IOM's five recommendation categories listed in Table 3.1. This discussion also describes IOM's underlying approach to formulating payment areas for GPCI components. Because the fourth and fifth recommendation categories are already a part of FY 2012 GPCIs, evaluations in this report are limited to the first three recommendation categories.

3.1 Recommended Changes to the Employee Wage Index

IOM proposes three main revisions of the employee wage index (EWI). First, IOM recommends replacing the current locality-based payment areas with commuting-adjusted payment areas. Applying this commuting-based smoothing algorithm produces county-level payment areas. Second, IOM recommends using wage data for workers in the healthcare industry, rather than wage data for workers across all industries. Third, IOM endorses the current construction of the employee wage index using the full range of occupations employed in physicians' offices.

The following discussion provides a detailed explanation of these recommendations. Sections 3.1.1, 3.1.2, and 3.1.3 describes IOM's proposed revisions to the employee wage index labor market payment areas. These sections describe IOM's approach for specifying labor market payment areas, provide a numerical example for calculating the EWI, and present discuss three alternative commuting-based smoothing algorithms proposed by IOM. Next, Section 3.1.4 describes IOM's recommendations related to the data sources to be used for calculating GPCI employee wage indices; the discussion both considers IOM's proposal to include only healthcare worker wages in the employee wage index and IOM's endorsement of the use of all available occupations when calculating the employee wage index.

3.1.1 Redefining Labor Market Payment Areas

IOM's proposal redefines payment areas for the employee wage index so that values differ by county. Although Recommendation 2-1 makes it appear that IOM proposes using MSAs to measure wages for labor markets, the implementation of IOM's smoothing adjustment (Recommendation 4-1) creates payment areas where EWI values vary for counties within the same MSA. The following two sections describe IOM employee-wage payment areas; the first presents an overview of how IOM proposes calculating the employee wage index using its new payment area specification, and the second provides a formal mathematical representation.

Description of IOM's Commuting-Based Smoothing Approach

Under the current 89 locality-based payment areas, there exists substantial variation in the costs of employing physician office staff. By using localities to define physician practice labor markets, the current payment area definitions may not adequately represent homogenous input markets. Medicare payments to hospitals, for example, use more narrowly-defined payment areas, comprised of 441 labor markets (made up of MSAs and rest-of-state, non-MSAs). Another challenge in formulating payment areas concerns producing large employee wage index differences between adjacent physicians' offices (i.e., cliffs). Since the current employee wage index only has 89 localities, the problem of wage index cliffs can be quite severe.

To address these challenges, IOM recommends redefining employee-wage payment areas and the calculation of wage indices following a four-step methodology:

(1) Compute the mean/median hourly wage (*MHW*) for each MSA;
(2) Calculate an area index wage for each county based on out-commuting patterns;
(3) Assign an index wage to each physician office based on its county location; and
(4) Normalize physician office wage measures to produce the EWI.

The first step uses BLS OES wage data to estimate the mean/median wage for each MSA. This step essentially replicates the current employee wage index methodology, but calculates a wage index value at the MSA rather than the locality level. Whereas current policy calculates *MHW* as the median hourly wage by payment area, IOM suggests making GPCI wage calculations comparable to those used to determine wage payments to hospitals, which sets *MHW* equal to the mean (average) hourly wage. IOM does not explicitly specify whether MSA wage levels should be measuring using means or medians. The analysis below switches between these two candidates for *MHW* depending on the context of the discussion.

The second step applies the commuting-based smoothing adjustment to create commuting-adjusted area index wages for each county. Specifically, these commuting-adjusted county index wages are equal to a weighted average of the *MHW* values calculated in the first step, where the weights are county-to-MSA *out-commuting* patterns.[17] IOM's out-commuting-based weights are defined as the share of workers who live in a county where the physician office is located who commute out to work in a physician office in another MSA.[18] This modification differs from an *in-commuting* adjustment, which is based on the share of workers who are employed at physician offices (or area where offices are located) who commute from other areas. This distinction is crucial and is addressed later in the report.

[17] Although the IOM report uses county-to-county commuting patterns, only county-to-MSA commuting patterns affect wage index values because the area index wages calculated in step 1 are identical for all counties in the same MSA.
[18] This proposal is similar to the out-migration adjustment CMS currently applies to certain counties under the hospital wage index (HWI). Section 505 of Public Law 108-173 permits CMS to adjust county HWI values for non-reclassified hospitals based on the share of workers who commute from each county to counties with higher wage index values.

The third step sets each physician office wage measure equal to the estimated area index wage (calculated in step 2) of the county in which the office is located. Because the out-commuting adjustment in step 2 varies by county, employee wage index values—and thus the PE GPCI as a whole—also vary by county, including counties within the same MSA.

The final step creates the EWI values. This step normalizes these out-commuting-adjusted wage measures by dividing each physician's wage measure by the average wage measures for all offices nationwide. This step produces an EWI index whose PE RVU-weighted average value equals 1.

IOM recommends using the same commuting-adjusted labor markets for both the PE GPCI employee wage index and the hospital wage index (HWI). Whereas CMS uses the EWI to adjust physician payments for regional variation in labor costs, CMS uses the HWI to adjust payments to institutional providers for variation in labor costs. IOM contends that using the commuting-adjusted system for both the HWI and the EWI is advantageous because hospitals and physicians compete for the same pool of workers. Moreover, IOM argues that standardizing the labor market definition across hospitals and physician practices "…is in line with increasing integration of hospital and physician care settings and the movement toward more accountable and coordinated health care across both settings."[19]

Formal Specification of IOM's Employee Wage Index

To explain the IOM EWI more precisely, the following discussion presents a mathematical representation of each of the four IOM steps described above. The first step calculates the *MHW*. Depending on whether *median* or *mean* BLS OES hourly wage estimates are used, the *MHW* would be defined as follows:

(3.1) $$MHW_m = \text{median}\langle \omega_j \text{ for } j \in \{m\}\rangle \quad \text{or} \quad MHW_m = \sum_{j \in \{m\}} e_{jm}\, \omega_j .$$

In these relationships, the notation $j \in \{m\}$ signifies that all physician practices located in MSA *m* are included in the calculations; in the second expression averaging is done with weights e_{jm} that measure physician practice *j*'s relative size in MSA *m*; and ω_j equals the hourly wage paid by physician practice *j*.[20] BLS OES data directly reports both median and mean measures of hourly wage data at the MSA level.[21]

[19] IOM 2011, pages 2-28.
[20] More specifically, the term e_{jm} denotes the number of workers employed in physician practice *j* in MSA *m* divided by the total number of physician practices employees in the MSA. This formulation ignores the fact that BLS receives wage data from establishments based on the number of employees in 12 consecutive, non-overlapping wage bands. For more details on the BLS survey methods (see http://www.bls.gov/oes/current/methods_statement.pdf)
[21] In practice, BLS does not observe individual worker level data, but uses wage bands. To estimate the median area wage, BLS (i) identifies the number of workers in each wage band, (ii) locates the wage band containing the 50th

The second step creates an area index wage for each County k (W_k^*) computed as a weighted average of MSA wages with weights serving as out-commuting shares, defined as the fraction of workers living in County *k* that commute to corresponding MSAs. Equation (3.2) describes this computation, which applies the smoothing adjustment using out-commuting patterns:

$$W_k^* = \sum_{m \in M_k} Z_{km} \times MHW_m \tag{3.2}$$

where $m \in M_k$ in equation (3.2) identifies the set of all MSAs *m* that contain physicians to which workers living in County *k* commute; and Z_{km} equals the share of workers residing in County *k* who commute to a physician office located in MSA *m*.

The third step then assigns the estimated county index wage from Step 2 to all physicians located in County *k*:

$$\omega_j^* = W_k^* \quad \text{for} \quad j \in \{k\}, \tag{3.3}$$

where the notation $j \in \{k\}$ denotes the set of all Physicians *j* located in the County *k*. Thus, all physicians located in the same county receive the same GPCI wage index.

Finally, the fourth step computes the GPCI employee wage index for a physician office *j* (EWI_j) as the GPCI wage measure for the physician from Step 3 divided by the national average GPCI wage index:

$$EWI_j = \frac{\omega_j^*}{\overline{\omega}} \tag{3.4}$$

where

$$\overline{\omega} = \frac{\sum_k W_k^* \times RVU_{PE,k}}{\sum_k RVU_{PE,k}}.$$

The national GPCI wage index $\overline{\omega}$ is weighted by the relative size of physician offices in counties with size measured by the number of PE RVUs in each county ($RVU_{PE,k}$).

3.1.2 IOM Employee Wage Index: A Numerical Example

To illustrate the four steps to calculate IOM's employee wage index, consider the following example. Assume there are five counties with physician practices (Counties *A*, *B*, *C*, *D*, and *E*).[22] These five counties are located in three MSAs; MSA *a* contains County *A*; MSA *b* contains Counties *B* and *C*; and MSA *c* contains Counties *D* and *E*. Workers can commute from any one of the five counties to physician practices located in each of these counties.

percentile hourly wage rate, (iii) estimates the 50th percentile wage rate using a linear interpolation procedure. For more information, see http://www.bls.gov/oes/current/methods_statement.pdf.

[22] Even if there are multiple physician practices in each county, there is no loss of generality because the IOM smoothing adjustment takes place at the county level. To simplify the exposition, the following examples assume that healthcare workers employed outside of the offices of physicians industry do not affect *MHW* values.

The first step of the IOM employee wage index methodology calculates the *MHW* for each MSA. All counties within an MSA, however, are assigned the MSA's *MHW* value under this step. In Table 3.3, column 1 lists each county, and column 2 lists the MSA in which the county is located, respectively. Column 3 shows the number of practice expense RVUs in each county, and column 4 gives the percentage of PE RVU in each county. For instance, physicians located in County *C* perform services that make up 25 percent (5.0/20) of the PE RVUs nationally. Column 5 displays the *MHW* in each county (MHW_k). For simplicity, this example measures wages for a single occupation, although in practice *MHW* would be a composite measure as described in Appendix A. Currently, CMS uses wage data from the BLS OES. Since the publicly available BLS OES data are only available at the MSA level, all counties within the same MSA have the same *MHW* value.

Table 3.3: Illustrating Step 1 of the IOM Employee Wage Index Calculation

County (k)	MSA (m)	PE RVU (in millions)	% of PE RVUs	Median Hourly Wage (MHW_k)
A	*a*	0.5	2.5%	24.00
B	*b*	6.0	30.0%	28.50
C		5.0	25.0%	28.50
D	*c*	4.5	22.5%	37.00
E		4.0	20.0%	37.00

The second step of IOM's employee wage index calculation creates a county index wage (W_k^*) that incorporates the smoothing adjustment. Table 3.4 illustrates these calculations. Columns 1, 2, and 3 display the county where each worker lives, the MSA to which each worker commutes, and the MHW in the MSAs to which these workers commute, respectively. Column 4 displays the county-to-MSA out-commuting shares (Z_{km}). For County *A*, this column indicates that 50 percent of County *A* resident workers commute to work in physician offices located in MSA *a*, 20 percent commute to offices located in MSA *b*, and 30 percent commute to offices located in MSA *c*. Column 5 calculates the commuting-adjusted county index wage. For County *A*, one can calculate its commuting-adjusted index wage as: W_A^* = 24.00×50% + 28.50×20% + 37.00×30% = 28.80.

Table 3.4: Illustrating Step 2 of the IOM Employee Wage Index Calculation

County Where Worker Lives (k)	MSA Where Worker is Employed (m)	Median Hourly Wage (MHW_k)	County-to-MSA Commuting Shares (Z_{km})	Commuting-Adjusted Index Wage (W_k^*)	IOM's Employee Wage Index (EWI_k)
A	*a*	24.00	50%	28.80	0.926
	b	28.50	20%		
	c	37.00	30%		
B	*a*	24.00	20%	30.15	0.970
	b	28.50	50%		
	c	37.00	30%		
C	*a*	24.00	30%	28.85	0.928
	b	28.50	50%		
	c	37.00	20%		
D	*a*	24.00	20%	32.70	1.052
	b	28.50	20%		
	c	37.00	60%		
E	*a*	24.00	15%	33.78	1.086
	b	28.50	15%		
	c	37.00	70%		

The third step sets each physician office wage measure equal to the commuting-adjusted county index wage calculated in Step 2 of the county in which the office is located. For example, physician offices located in County *A* would receive a physician office wage measure of 28.80, while physician offices located in County *B* would receive a physician office wage measure of 30.15.

The fourth and final step renormalizes the physician office wage measures assigned in the third step to create IOM's employee wage index for each County k (EWI_k). Specifically, the fourth step renormalizes physician office wage measures (i.e., commuting-adjusted index wages, W_k^*) by dividing each value in column 5 of Table 3.4 by the national average commuting-adjusted wage index. The national average commuting-adjusted wage index is found by multiplying column 5 of Table 3.4 by the share of PE RVU's nationally (from column 4 of Table 3.3) and summing the resulting terms. In this example, the national average commuting adjusted wage index is 31.09 (28.80×2.5% + 30.15×30.0% + 28.85×25.0% + 32.70×22.5% + 33.78×20.0% = 31.09). To calculate the EWI for physician offices in each county, one simply divides W_k^* by 31.09. For instance, the EWI value for County *A* is 28.80 ÷ 31.09 = 0.926.

3.1.3 IOM's Three Smoothing Specifications

In addition to the baseline smoothed wage index described above, IOM proposes two additional models that apply the smoothing adjustment on a more limited basis. Thus, in total, IOM proposes the following three smoothing adjustment models:

- Model 1 (baseline): Apply smoothing adjustments to all counties.
- Model 2: Apply smoothing adjustments only where at least 10 percent of workers commute to a county in a different MSA.
- Model 3: Apply smoothing adjustments only where at least 10 percent of workers commute to a county in a different MSA and where the smoothed county wage index (W_k^*) is higher than the index of the home county.

To illustrate how the application of these models could affect employee wage index values, consider the application of the IOM smoothing adjustment to County *B* under each of the three IOM models. Table 3.5 displays county-to-county out-commuting shares. The first three columns list workers' county of residence, their MSA of employment, and each MSA's employee wage index under the current methodology (i.e., MHW_m). The fourth column displays the workers' county of employment, and the fifth column displays the county-to-county out-commuting shares. Note that workers who "out-commute" to County *B* work in the same county in which they live. The last three columns give the relevant county-to-MSA commuting share depending on which model is selected. To calculate IOM's smoothed county index wage (W_k^*) under all three models, one multiplies each MHW_m by the relevant county-to-MSA commuting share (Z_{km}) and sums them. For instance, Model 1's calculated W_B^* equals: \$24.00×20% +\$28.50×50% + \$37.00×30% = \$30.15.

Table 3.5: Application of Smoothing Adjustments under Three IOM Outmigration Models

County where Worker Lives (k)	MSA Where Worker is Employed	Median Hourly Wage (MHW_m)	County of Employment	County-to-County Commuting Shares	County-to-MSA Commuting Shares (Z_{km})		
					Model 1 (Baseline)	Model 2	Model 3
B	*a*	\$24.00	*A*	20%	20%	20%	0%
	b	\$28.50	*B* *C*	35% 15%	50%	56%	76%
	c	\$37.00	*D* *E*	24% 6%	30%	24%	24%
Commuting-Adjusted Wage Index (W_k^*)					\$30.15	\$29.64	\$30.54

Although Model 1 (baseline) only requires county-to-MSA commuting data to calculate the relevant county-to-MSA commuting share, Models 2 and 3 require county-to-county commuting data. Under Model 2, for example, the County *B*-to-MSA *c* commuting share is set equal to the County *B*-to-County *D* commuting share because fewer than 10 percent of County *B* residents commute to County *E*. In essence, the out-commuting shares between Counties *B* and *E* are reallocated to the non-commuting areas (i.e., County *B*-to-County *B*). Model 3 introduces an additional modification, in which workers must commute to labor markets where the wage index is higher than the index of the home county. As a result, in Model 3 the County *B*-to-MSA *a* commuting share receives a weight of 0 percent because workers who commute from County *B* to MSA *a* are commuting to a payment area with a lower employee wage index. In Model 3, out-commuters who work in lower wage areas are not included in the out-commuting adjustment. The County *B*-to-MSA *c* commuting shares, however, are identical under Models 2 and 3 (24 percent) because MSA *c* has a higher EWI than County *B*.

The remainder of this report only examines the baseline (Model 1) smoothing specification. IOM does not identify a preference for any one of these three models, and since Models 2 and 3 are, in essence, a more limited application of Model 1, this paper focuses on this baseline model. Thus, all empirical evaluations in subsequent chapters rely on implementing the IOM EWI payment areas using the Model 1 specification.

3.1.4 Wage Measurement Recommendations

The IOM recommendations touch on two dimensions for how the EWI measures wages in each labor market. First, IOM advises CMS to measure regional variation in employee labor costs using wage data for workers in the healthcare industry, rather than wage data for workers across all industries (Recommendation 2-2). Under this recommendation, the wage measured for registered nurse occupation would only include the wages of nurses employed in healthcare industries such as physician offices and hospitals, but would exclude nurses that are employed in other industries, (e.g., school nurses), from the EWI wage measurement. The IOM report states that, although all-industry wage data has the largest sample size, IOM "is concerned that the [all-industry] sample does not represent physician offices." Using industry-specific occupation wage data by MSA, however, requires access to confidential BLS OES data. IOM proposes that CMS secure an agreement with BLS to use confidential OES data (Recommendation 5-5). Accessing these data would permit CMS to calculate regional variation in employee wages by using healthcare-industry wage data for workers employed in the offices of physician industry.

The second dimension of IOM's employee wage measurement recommendation endorses the EWI's current use of the full range of occupations employed in physicians' offices. In the Sixth Update of the GPCI, the employee wage index was based only on four BLS OES occupation groups: (i) registered nurses; (ii) office, admin support; (iii), licensed practical & licensed vocational nurses; and (iv) health care technical & medical assistants & other healthcare.[23] The Revision to the Sixth Update, however, substitutes the four occupational categories used in the Sixth Update with the occupations representing 100 percent of total non-physician wages in the offices of physicians industry.[24] The 2010 BLS OES data contains wage and employment information for 269 occupations in the offices of physicians industry. Because IOM endorses the current CMS approach for selecting the occupations to be used in the employee wage index, the remainder of the report will not directly evaluate this recommendation.

3.2 Recommended Changes to Measurement of Physician Wages

IOM recommends using a regression-based methodology to measure regional variation in physician wages. Table 3.6 summarizes describes how the IOM proposal would affect the methodology CMS current uses to compute the PW GPCI. As describe in Section 2.3.1, CMS's current methodology relies on four steps: (1) select proxy occupations and calculate an occupation-specific county-level index for each county; (2) assign weights to each proxy-occupation index based on the occupation's national share of wage bill; (3) apply a 25 percent work adjustment (also known as the 'inclusion factor') to the proxy-occupation index; and (4) adjust the values for budget neutrality. IOM's recommendations make changes in only the first three steps.

Table 3.6: Summary of Changes to PW GPCI Components

PW GPCI Component	Current PW GPCI	IOM's Recommendations
Proxy Occupations	Seven occupational groups intended to measure wages for professional workers	Can use current or an alternative set of proxy occupations
Occupation Weights	National wage shares	Correlation with physician wages
Inclusion Factor	25%	Sum of regression model's coefficients for the proxy occupations variables
Budget Neutrality Adjustment	Normalize index so that PW RVU-weighted average PW GPCI equals 1.0	Normalize index so that PW RVU-weighted average PW GPCI equals 1.0

IOM endorses continued use of proxy occupations to calculate the PW GPCI, but recommends replacing the current PW GPCI occupational weighting methodology by a regression-based approach to compute weights. A representation of this regression takes the form:

(3.5)
$$y_r = \beta_0 + \sum_{g=1}^{G} \beta_g x_{gr} + \epsilon_r$$

[23] O'Brien-Strain et al. November 2010.
[24] MaCurdy et al. October 2011.

where the dependent variable y_r measures physician wages in region r relative to the national average wage; β_0 and β_g are regression coefficients; x_{gr} represent the wage of proxy occupation group g in region r measured relative to the national average wage for occupation group g; and ϵ_r denotes an error term capturing unobserved factors. Observations in this regression are regions, which depend on the level of detail at which wage data are reported. Current GPCI policy interprets r as locality payment areas. Adoption of IOM's Recommendation 2-1 implies that r would correspond to an MSA.

Use of this regression framework would affect the first three steps listed in Table 3.6. Regarding the first step, IOM recommends that CMS use the empirical model to validate the proxies currently used in PW GPCI calculations. One approach for doing this would be to perform familiar F-tests to evaluate the impacts of including alternative occupational compensations as covariates, adding those with significant predictive effects and yielding high levels of correlation or R-squared. If candidate proxy wage data are not found to have sufficient predictive power for physician compensation, IOM suggests calculating the PW GPCI directly using physician wage data rather than wages from proxy occupations.

Turning to the second step, IOM recommends weighting each occupation g based on its correlation with physician earnings measured by its regression coefficient, β_g. Proxy occupations that exhibit a high correlation with physician wages would be given a larger weight; a low correlation, on the other hand, suggests that the reference groups could not serve reliably as proxies and hence less weight would be applied to this profession's index value. Estimated regression coefficients would replace an occupation's wage bill share as the proxy occupation's weight in the PW GPCI.

With respect to the third step, the relationship between the regression coefficients and the inclusion factor can be expressed as

$$\hat{y}_r = \beta_0 + \alpha^* \sum_{g=1}^{G} \alpha_g x_{gr} \tag{3.6}$$

where $\hat{y}_r$ equals the fitted value of physician hourly earnings y_r; and the coefficients

$$\alpha^* = \sum_{g=1}^{G} \beta_g \quad \text{and} \quad \alpha_g = \beta_g / \alpha^*.$$

According to the IOM report, the term α^* mimics the inclusion factor in the current PW GPCI methodology, and the summation

$$\sum_{g=1}^{G} \alpha_g x_{gr}$$

corresponds to an index with a weighted average set to 1. Since the regression specifications in equations (3.5) and (3.6) are equivalent, their predicted values are the same.

Finally, the fourth step rescales the PW GPCI to ensure budget neutrality. This step remains unchanged from the current PW GPCI methodology.

3.3 Recommended Changes to Data Sources Used to Compute Office Rents

To estimate the office rent index for CY 2012, CMS currently uses residential rent data from ACS.[25] CMS uses 3-year 2006-2008 ACS rent data for CY 2012. Rents in each locality are measured based on gross rents (i.e., rent plus utility costs) for two-bedroom residences. Using two-bedroom rents partially adjusts the rent estimates for regional variation in housing size by removing variation in rents due to the geographic variation in the number of bedrooms per residence. Prior to CY 2012, CMS relied on rent estimates from the HUD Fair Market Rents (FMR).[26]

Rather than use residential rent data to estimate the office rent index, IOM recommends using rental data from commercial properties. Before arriving at this recommendation, IOM identified and evaluated several alternative public and commercially available sources of data to determine whether an accurate alternative is available to replace the residential rent data currently in use. These sources include HUD, American Housing Survey, General Services Administration (GSA), Basic Allowance for Housing (U.S. Department of Defense), U.S. Postal Service (USPS), Medical Group Management Association (MGMA) Physician Cost Survey for Single Specialty Practice, and REIS, Inc. After evaluating the characteristics of these data, including the frequency and methods of data collection, sample sizes, and demographic information, IOM concludes that these sources all have substantial limitations.[27] IOM also considered adding a question on commercial rent prices to an existing federal survey, but determined the costs of collecting these data would be prohibitive. Thus, although IOM recommends using a commercial rent data to calculate the office rent index, they do not identify a viable data source CMS could use.

[25] CMS's decision to use the ACS data for CY2012 follows a recommendation in a previous Acumen report (MaCurdy et al. October 2011). The report argues in favor of using commercial rent data to calculate the PE GPCI office rent index. However, due to a lack of suitable commercial office rent data, the report recommends the continued exploration of viable sources of commercial rent data.

[26] The primary use of the HUD FMR is to determine payment standards for HUD programs, such as Section 8 contracts and the Housing Choice Voucher program. The FY 2011 FMR estimates are based partially on 2000 Census data. To arrive at the final FMR estimates, HUD adjusts the 2000 Census data using 2008 ACS rent estimates and then further adjusts using CPI rent and utilities price indices. Although HUD data are displayed at the county level, they are derived from MSA estimates; thus the HUD data allocate the FMR estimate to each county in the MSA.

[27] Limitations mentioned by IOM include lack of representativeness of the market in which physicians rent space, small sample size, low response rates, and sample biases.

3.4 Endorsement of Current Purchased Services Index Methodology

IOM advises CMS to continue the use of the purchased services index to adjust for geographical differences in nonclinical labor-related expenses. CMS introduced the purchased services index in in CY 2012.[28] Prior to this, the GPCI methodology only measured regional variation in wages for workers that physician practices employed directly but did not measure regional variation of other contracted services such as accounting, advertising, consulting, landscaping etc. With the new purchased services index, the regional cost variation in the MEI expense categories "All Other Services" and "Other Professional Expenses" can now be adjusted. The purchased services index assumes that the cost of capital for these contracted firms is constant across the nation. Thus, each GPCI's purchased services index value includes a labor cost component that varies regionally and a capital component which is normalized to 1.000 for all areas.[29]

3.5 Endorsement of Current GPCI Cost Share Weights

GPCI cost share weights determine the relative importance for each type of physician expense calculated as part of the GPCI methodology. Currently, CMS assigns a cost share weight to each GPCI based on its corresponding MEI weights. The MEI weights estimate the share of physician expenses broken down into the physician work, PE (i.e., non-physician employee compensation; office rent; purchased services; and equipment, supplies and other categories) and malpractice insurance categories for the average American self-employed physician. To calculate the PE GPCI, a separate index is first calculated for each of the four practice expense categories. The weights are then calculated for each of these indices by the PE cost share weight, which is derived from the MEI cost share weights. While CMS calculated GPCI cost shares from 2000-based MEI data in CY 2011, the Final Revisions to the Sixth Update report recommends updating GPCI cost share weights to coincide with the 2006-based MEI cost share weights going forward.[30] Table 3.7 compares the cost share weights used to adjust physician payments in 2011 and 2012, which were based on 2000 and 2006 MEI data respectively. For CY2012, the physician work, PE, and malpractice insurance GPCI components are assigned cost share weights of approximately 48 percent, 47 percent, and 4 percent respectively. Per statutory requirement, the MEI weights are updated annually.

---

[28] See MaCurdy, et al. October 2011 for more details on the purchased services index.
[29] Ibid

[30] The Revision to the Sixth Update describes the motivation for updating GPCI cost share weights using the 2006-based MEI and the associated impact.

IOM endorses the current MEI-based GPCI cost share weights and finds the statutory requirement to use the MEI cost share weights as the source of GPCI cost share weights to be reasonable and therefore should be continued.

Table 3.7: Cost Share Weights Used in 2000-Based and 2006-Based MEI

Expense Category	Cost Share Weights %	
	2011	2012
Physician Work	**52.466**	**48.266**
Practice Expense	**43.669**	**47.439**
Employee Compensation	*18.654*	*19.153*
Office Rent	*12.209*	*10.223*
Purchased Services	*N/A*	*8.095*
Equipment, Supplies, and Other	*12.806*	*9.968*
Malpractice Insurance	**3.865**	**4.295**
Total	**100.000**	**100.000**

4 EVALUATION OF GPCI EMPLOYEE WAGE RECOMMENDATIONS

IOM proposes two notable changes that would alter the current employee wage index methodology. First, IOM recommends redefining payment areas for the employee wage index accounting for worker commuting patterns, which mirrors its proposed changes to the hospital wage index. IOM's payment area revisions would permit employee wage index values to vary across counties, including counties located within the same MSA. As a result, the IOM proposal would potentially increase the number of employee wage index payment areas from 89 to over 3,000 depending on the smoothing option selected. Second, IOM proposes that CMS measure wages within each payment area using wage data for workers employed in the healthcare industry rather than in all industries as is currently done. Since industry-specific wage data by MSA are not publicly available in the BLS OES, IOM recommends that CMS develop an agreement with BLS to analyze its confidential micro healthcare-industry wage data by region and share its results with CMS.

The following discussion evaluates these two recommended changes. Section 4.1 conducts a conceptual evaluation of IOM's proposed revisions to the payment areas for constructing employee wage indices. This section relies on a simple three-county framework to highlight the principal features of IOM's out-commuting adjustment. Next, Section 4.2 assesses whether IOM's proposed smoothing adjustments reduce the frequency wage index cliffs. In this section's empirical application, cliffs are defined large differences in employee wage index values between nearby counties. Section 4.3 assesses IOM's proposal to use wages from the healthcare industry to compute the employee wage index. Because BLS OES data for this industry is confidential and not publically available, this section's evaluation is limited to a conceptual—rather than empirical—analysis of the advantages and disadvantages of using healthcare industry wage data to calculate the employee wage index.

4.1 Characterization of IOM's Recommended Payment Areas for Labor Markets

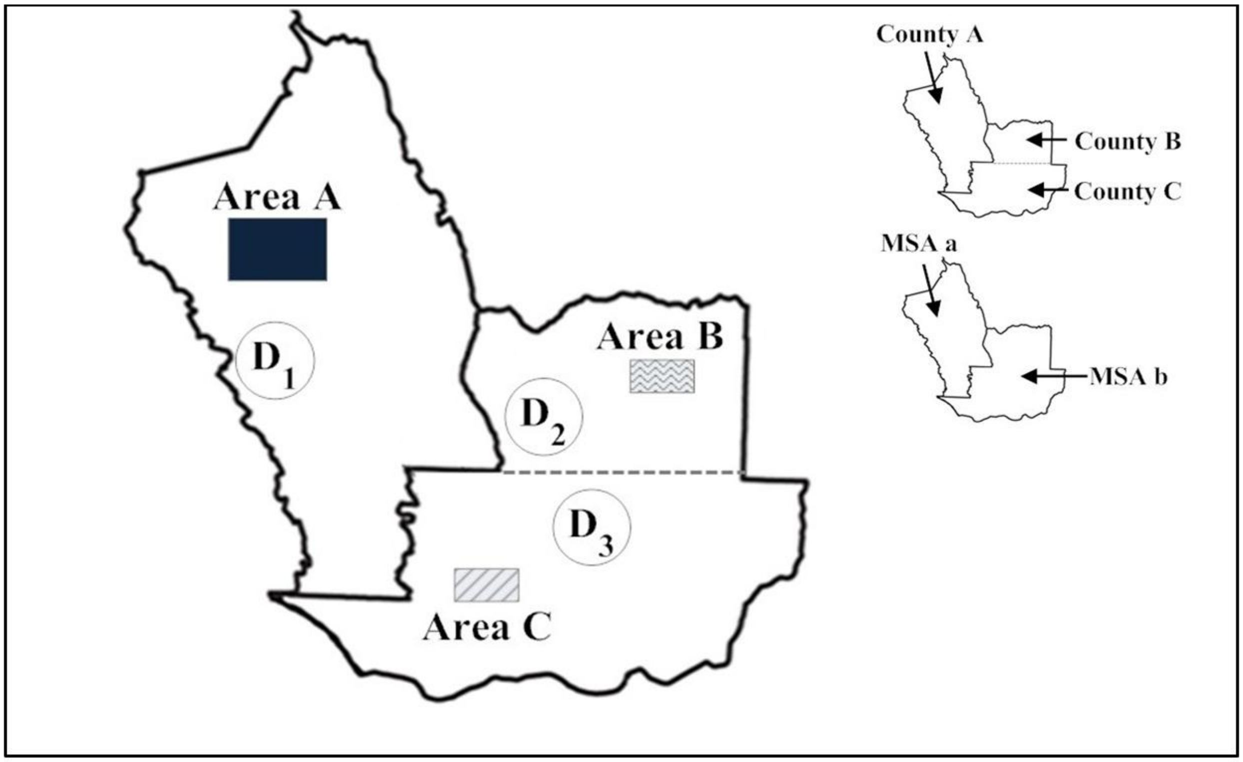
To evaluate IOM's suggested changes to the employee wage index labor payment areas, the following discussion introduces a simple three-county physician practice labor market to illustrates the factors relevant in specifying wage indices for physician offices. This characterization includes a description of how commuting patterns can be used to define a physician office's labor market and calculate a physician office's employee wage index. The discussion summarizes the relationships linking the wage rates of physician offices and regions and specifies employee wage index formulations used to measure trends in physician offices' labor costs. Using this characterization of physician practices' labor markets, this section evaluates IOM's proposed out-commuting-based employee wage index and provides examples to illustrate how the IOM index can systematically over- or under-estimate the true wage level a physician's office faces.

The remainder of this section contains four parts. Section 4.1.1 presents a simple characterization of a labor market for healthcare workers and introduces a basic framework for understanding the forces that shape a physician office labor market. Section 4.1.2 discusses how one can calculate IOM's proposed commuting-adjusted employee wage index within this example. Section 4.1.3 discusses the advantages and disadvantages of using a smoothing adjustment that relies on worker out-commuting proportions. Finally, Section 4.1.4 presents two examples that illustrate the types of problems potentially encountered due to IOM's approach.

4.1.1 Simple Depiction of Labor Markets for Physician Offices

To facilitate the conceptual discussion of the IOM employee wage index, the following discussion presents a simple characterization of a physician office labor market comprised of three physician offices and three counties. The large illustration on the left in Figure 4.1 depicts the labor markets faced by Physician Offices *1*, *2*, and *3*, where these offices are represented by the circles D_1, D_2, and D_3. The two smaller illustrations on the right in Figure 4.1 identify county and MSA boundaries. One physician office is located in each of Counties *A*, *B*, and *C*, where County *A* is located in MSA *a*, and Counties *B* and *C* are located within MSA *b*. For simplicity, assume that each MSA is also a Medicare locality. Within the three counties, physician offices employ workers living in three residential areas (Areas *A*, *B*, and *C*), represented by the shaded rectangles. County *A* has a larger workforce than Counties *B* and *C*, and this is represented by the larger size of the box of Area *A* in County *A*. All physician offices can draw workers from any of the three counties.

Figure 4.1: Illustration of Local Labor Markets for Three Physician Offices



Commuting data directly link physician office wages and area wages through two simple mathematical relationships. To quantify employment patterns for the purpose of developing these linkages, designate ℓ_{1A}, ℓ_{1B}, and ℓ_{1C} as the amounts of labor hired by Physician Office *1* from Areas *A*, *B*, and *C*, respectively. These labor-unit measures could represent either the number of workers or total hours of employment. Assuming Physician Office *1* draws all of its labor from Areas *A*, *B* and *C*, its total labor force is $\ell_1 = \ell_{1A} + \ell_{1B} + \ell_{1C}$. The implied share of labor that Physician Office *j* hires from an Area *k* equals:

(4.1) $S_{jk} = \frac{\ell_{jk}}{\ell_j}$ = proportion of Office *j*'s workers from Area *k* (in-commuters).

Correspondingly, the total number of workers employed across all three physician offices and living in Area k equals $L_k = \ell_{1k} + \ell_{2k} + \ell_{3k}$,[31] and the share of labor residing in Area k and hired by Physician Office j equals:

(4.2) $P_{jk} = \dfrac{\ell_{jk}}{L_k}$ = proportion of Area k's workers commuting to Office j (out-commuters).

The term "in-commuting" refers to the shares S_{jk} that measure the in-coming rates from areas, whereas the term "out-commuting" refers to the shares P_{jk} that measure out-going rates from areas.

Two identities link commuting shares, physician office wages, and area wages. The first identity demonstrates that a physician office's average wage level can be expressed as a weighted average of area wages, where the weights depend on in-commuting shares. Defining ω_j as the average wage rate paid by Physician Office j, one can verify that

(4.3)
$$\omega_j = \sum_{k \in \{A,B,C\}} S_{jk} W_{jk}$$

where W_{jk} equals the average wage paid by Physician Office j to its workers who live in Area k.[32] A distribution of wages exists in each area, with the variability in wages reflecting differences needed to entice workers to seek employment at each candidate physician office. The literature often calls these differences "compensating wage differentials," which account for a variety of factors such as commuting costs; for example, a physician office farther away from an area typically must pay a higher wage to that area's residents to compensate them for the higher travel costs associated with working at the more distant physician office. Relationship (4.3) shows that if area wages and commuting patterns are known for each physician office, one can readily compute a physician office's average hourly wage.

The average wages workers receive in a given residential area analogously depend on the wages individual physician practices pay. Defining W_k as the average wage rate earned by physician office workers residing in Area k, one can verify

(4.4)
$$W_k = \sum_{j \in \{1,2,3\}} P_{jk} \omega_{jk}$$

[31] The quantity $L = \sum_{j \in \{1,2,3\}} \ell_j = \sum_{k \in \{A,B,C\}} L_k$ equals the size of the total labor force working in all physician offices and, equivalently, the size of the total labor force living in all residential areas.

[32] Thus, the values of W_{1A}, W_{1B}, and W_{1C} represent the average wages Physician Office *1* pays its workers who live in Areas *A*, *B*, and *C*, respectively.

where ω_{jk} denotes the average wage for workers employed by Physician Office *j* who live in Area *k*.[33] If one assumes that all physician offices pay their workers an identical wage regardless of location, the preceding equation simplifies to:

$$W_k = \sum_{j \in \{1,2,3\}} P_{jk}\, \omega_j \quad . \tag{4.5}$$

Recall that the terms P_{jk} measure out-commuting shares between areas and physician offices.

4.1.2 Calculation of IOM Employee Wage Index in this Example

Calculating the IOM employee wage index for Physician Offices *1*, *2*, and *3* follows the steps outlined in Section 3. For simplicity, this example assumes that physician offices employ workers from a single occupation and that workers employed in the same physician practice receive the same wage. Further, it ignores the case where healthcare workers employed outside the offices of physicians industry can influence the *MHW* values.

Applying the first step of the IOM methodology to this example involves calculating the *MHW* for MSA *a* (County *A*) and MSA *b* (Counties *B* and *C*). If we assume IOM uses a median *MHW* specification, one can calculate the *MHW* as follows:

$$MHW_a = \omega_1 \quad \text{and} \quad MHW_b = \begin{cases} \text{median}\langle \omega_j \text{ for } j = 2,3 \rangle \\ \text{mean}\langle \omega_j \text{ for } j = 2,3 \rangle \end{cases} = \frac{\omega_2 + \omega_3}{2} \text{ since } \ell_2 = \ell_3 \tag{4.6}$$

where MHW_m is the median hourly wage for MSA *m*, ω_j represents the wage rate paid to workers employed in Physician Office *j*, and ℓ_j is the number of workers employed in Physician Office *j* as defined above.

The second step under the IOM approach applies the proposed smoothing adjustment. In this example, one can calculate the implied values of the County *k* area wage index as follows:

$$W_k^* = Z_{ka}\, MHW_a + Z_{kb}\, MHW_b \qquad k = A, B, C \tag{4.7}$$

where W_k^* are IOM's estimated smoothed wage index values in County *k* and Z_{km} represents the share of workers residing in County *k* who commute to MSA *m*.

In the third step, IOM assigns each physician office a wage index equal to the area index computed for the county in which it is located, which in Figure 4.1 takes the form:

$$\omega_1^* = W_A^* \qquad \omega_2^* = W_B^* \quad \text{and} \quad \omega_3^* = W_C^* \tag{4.8}$$

Finally, in the fourth step, the physician office wage index values measured from the third step values are normalized so that EWI has a PE RVU-weighted average of one.

[33] By construction the average physician office wage for workers from a specific area equals the average area wage of workers who work at that physician office, so $\omega_{jk} = W_{jk}$.

4.1.3 Issues with IOM's Commuting Shares

A primary question encountered when creating a wage index is whether the index should measure wage levels for workers *employed* in a particular area or the wages of workers *living* in this area. As illustrated in the following example, IOM takes the latter approach given that it applies an out-commuting adjustment as opposed to an in-commuting adjustment when computing the employee wage index. The county-to-MSA commuting shares (Z) used in equation (4.7) to calculate the IOM EWI mirror the county-to-physician-office commuting shares (P) defined in equation (4.2).[34] In particular, the mapping between the Zs and Ps takes the form:

(4.9) $$Z_{ka} = P_{1k} \qquad Z_{kb} = P_{2k} + P_{3k} \qquad k = A, B, C.$$

These relationships have such a simple structure in this example because a single physician office is located in each county. Relationship (4.7) used by IOM to compute area wages takes the form of the general specification (4.5) for computing the average wage of workers living in an area. Thus, IOM's employee wage index in each county is proportional to the wage of workers who live in the county rather than the wage of workers employed in that county.

By creating an index that measures the wage level only of workers who live near a physician office rather than of all those who could potentially work at the physician office (including those who live far away from the physician office), IOM's approach has two limitations. First, some of the information used to compute the index value for a given physician office is based on the wages of workers employed outside of that office's labor market. Second, IOM's EWI value for a given physician office neglects market-relevant information regarding the wages of workers employed at that office but who live in a different county. For instance, if the in-commuting workers come from high-wage areas, this information should contribute to increasing the physician office's employee wage index value; if such workers live in low-wage areas, they should contribute to decreasing the physician office's employee wage index.

4.1.4 Illustrations of IOM's Out-Commuting Adjustment

Two examples presented below use Figure 4.1 to highlight the types of impacts potentially encountered due to the problematic features of IOM's out-commuting adjustment. The first example, which assumes physician offices compete across both urban and rural counties to attract workers, demonstrates that the IOM methodology can fail to capture the correct ordering of labor costs within an MSA; the smoothing algorithm can create cases where physician practices with high labor costs receive a lower employee wage index value than physician practices in the same MSA that face lower labor costs. The second example considers

[34] Note that the identity in equation (4.2) uses average wages whereas the EWI values calculated in equation (4.9) may rely on median wage data.

a situation where all workers commuting patterns cross political boundaries. In this example, a physician office's IOM employee wage index depends exclusively on the wages of workers who are employed in other MSAs. Although the out-commuting patterns assumed in these examples are extreme cases, they illustrate in a simple way some of the fundamental limitations inherent in a smoothing adjustment based on out-commuting rates.

Example 1: Urban and Suburban Physician Offices Competing for Workers across Regions

Suppose in Figure 4.1 that Physician Office *1* is a large practice in an urban county that draws workers from all areas; Physician Office *2* is a small practice in a suburban county that hires workers both from its local area and from the urban county; and Physician Office *3* is another small practice in a suburban county that hires workers only from its own county. Table 4.1 presents the employment levels, in-commuting shares, and out-commuting shares corresponding to this example. The first three columns of the table list the county where each worker lives, the practice where they are employed, and the MSA to which workers residing in each county commute to work. The fourth column lists the number of individuals who work at each practice, distinguished by their area of residence. The fifth column presents in-commuting shares, which measure the fractions of employees who work at a specific physician office and live in each of various areas. Physician Office *1*, for instance, draws 68.8% of its workers from County *A* (S_{1A} = 0.688), 6.3% of its workers from County *B* (S_{1B} = 0.063), and 25% of its workers from County *C* (i.e., S_{1C} = 0.25).[35] The sixth column reports out-commuting shares, which measure the fractions of workers residing in each county who work in each of various practices. For example, two thirds of workers living in County *C* work in Physician Office *1* (P_{1C} = 0.667), one third work at Physician Office *3* (P_{3C} = 0.333), and no workers living in County *C* commute to Physician Office *2* (P_{2C} = 0).

Table 4.1: Commuting Shares and Wages, Urban-Rural Example

County of Residence (*k*)	Physician Office of Employment (*j*)	MSAs where County Residents Work (*m*)	Number of Workers (ℓ_{jk})	In-Commuting Shares (S_{jk})	Out-Commuting Shares (P_{jk})
A (urban)	1	a	275	68.8%	91.7%
	2	b	25	50.0%	8.3%
	3	b	0	0.0%	0.0%
B (suburban)	1	a	25	6.3%	50.0%
	2	b	25	50.0%	50.0%
	3	b	0	0.0%	0.0%
C (suburban)	1	a	100	25.0%	66.7%
	2	b	0	0.0%	0.0%
	3	b	50	100.0%	33.3%

[35] These figures do not sum to 100 percent due to rounding.

Table 4.2 calculates the IOM's smoothed county index wage implied by this example. The table presents the wage rates paid by each physician office and the mean/median hourly wage for each MSA. Physician Office *1* pays its workers $30; Physician Office *2* pays its workers $26; and Physician Office *3* pays its workers $22. Thus, the *MHW* in MSA *a* is $30 and the *MHW* for MSA *b* is $24. Because Physician Offices *2* and *3* have the same number of workers (i.e., 50), the mean hourly wage and median hourly wage are identical in this example. If one assumes that localities in this example are defined by MSAs, then the current Medicare employee wage index is proportional to the *MHW* in each MSA. The *MHW* values are displayed in the sixth column of the table.

As discussed above, the IOM methodology computes a smoothed index wage value for each county as a weighted average of the *MHW* values, where the weights are the out-commuting shares. In County *A*, for instance, the smoothed county index wage equals $29.50 ($30.00×91.7% + $24.00×8.3%). All physician offices located in County *A* would receive this wage value. Column 7 of Table 4.2 lists the IOM EWI assigned to all three physician offices.[36]

In this example, the rank-ordering of IOM's smoothed county wage index values does not match the rank-ordering of the wages paid by physician practices. IOM's approach produces values indicating that Physician Office *3* faces higher costs than Physician Office *2*. The county index value for Physician Office *2* is now four percent lower than the relevant county index value for Physician Office *3*, even though Physician Office *2* faces wages costs that are nearly 20 percent higher than Physician Office *3*. Although the current CMS employee wage index approach does not distinguish between the circumstances faced by Physician Offices *2* and *3*—since this example assumes that localities are defined by MSAs *a* and *b*—it also does not incorrectly elevate the EWI values for Physician Office 3 above those of Physician Office 2.

Table 4.2: Calculation of the IOM EWI, Urban-Rural Example

Physician Office (j)	**Physician Office Wage (ω_j)**	**Worker County of Residence (k)**	**MSA where County Residents Work (m)**	**Out-Commuting Shares (Z_{km})**	**<u>Current EWI</u> Median Hourly Wage (MHW_m)**	**<u>IOM EWI</u> Smoothed County Index Wage (W^*_k)**
1	$30.00	A	a	91.7%	$30.00	$29.50
			b	8.3%		
2	$26.00	B	a	50.0%	$24.00	$27.00
			b	50.0%		
3	$22.00	C	a	66.7%	$24.00	$28.00
			b	33.3%		

[36] The EWI values in Column 6 and 7 of Table 4.2 are not normalized based on the national average EWI values. The "Current EWI" and "IOM EWI" values, however, are proportional to the final wage index values.

The failure of the IOM methodology to capture the correct ordering of labor costs across suburban Physician Offices *2* and *3* results directly from the out-commuting adjustment's two limitations described above. First, with regard to recognizing workers living in a locality but who commute outside of a practice's local labor market, the EWI value for Physician Office *3* counts the earnings of workers who commute to practices in County *A*, attracted by its higher compensation. Part of this higher compensation reflects a compensating differential paid to workers for travel costs and time spent commuting, and a case can be made that this extra compensation should not be fully credited to Physician Office *3*. Increasing the size of the worker pool living in County *C* and the corresponding share of these local workers commuting to County *A* would induce yet a higher value index value assigned to Physician Office *3* even if employment at this practice remains constant. Down-weighting the wages of out-commuting workers according to the share hired by the local practice would tend to lower the value of Physician Office *3*'s index, and this decrease in its index value would more closely reflect its lower labor costs compared to its suburban Physician Office *2* counterpart.

Second, with regard to recognizing a physician office's employment of workers living outside of its local community, the employee wage index for Physician Office *2* does not incorporate the extent that this provider hires workers living in the higher-cost urban County *A*. Accounting for the in-commuting from high-wage County *A* would tend to raise the value of Physician Office *2*'s index, and this increase in its employee wage index would more closely reflect its higher labor costs compared to its suburban Physician Office *3* counterpart.

Example 2: A Physician Office Hires Only from Outside its MSA

To illustrate another limitation of the IOM approach, consider a second example where some physician offices hire all of their workers from outside their own MSA. Figure 4.2 presents a case where a barrier, represented by the two-sided line, restricts County *C* workers to employment in Physician Office *1*. Workers cannot cross this barrier when traveling to employment. The barrier could reflect a variety of inhibiting factors such as: infrastructure (e.g., no roads exist), geology (e.g., a mountain range forms a natural barrier), or institutions (e.g., an extremely high toll makes commuting costs prohibitively high).

Figure 4.2: Illustration of Local Labor Markets with Commuting Barrier

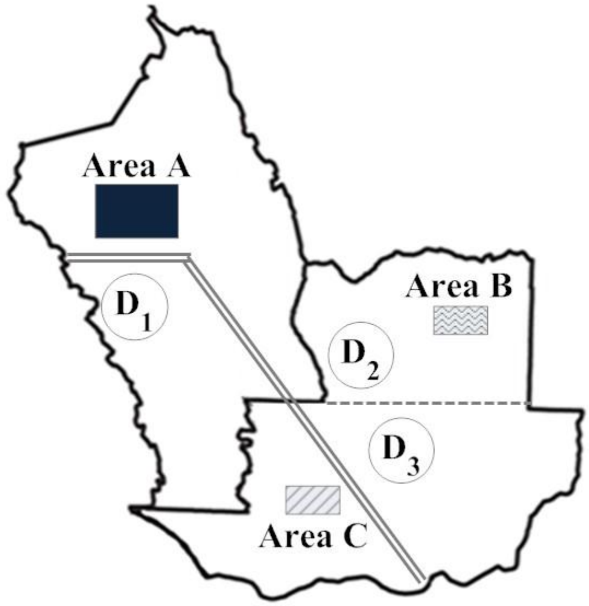


Table 4.3: Commuting Shares and Wages, Commuting-Barrier Example

Worker County of Residence (*k*)	Physician Office of Employment (*j*)	MSA of Employment (*m*)	Number of Workers (ℓ_{jk})	In-Commuting Shares (S_{jk})	Out-Commuting Shares (P_{jk})
A	1	a	0	0.0%	0.0%
	2	b	140	87.5%	70.0%
	3	b	60	60.0%	30.0%
B	1	a	0	0.0%	0.0%
	2	b	20	12.5%	33.3%
	3	b	40	40.0%	66.7%
C	1	a	110	100.0%	100.0%
	2	b	0	0.0%	0.0%
	3	b	0	0.0%	0.0%

Table 4.4: Counterintuitive Implication of IOM Smoothing, Commuting-Barrier Example

Physician Office of Employment (*j*)	Physician Office Wage (ω_j)	Worker County of Residence (*k*)	MSA where County Residents Work (*m*)	Out-Commuting Shares (Z_{km})	Current EWI Median Hourly Wage (MHW_m)	IOM EWI Smoothed County Index Wage (W_k^*)
1	$30.00	A	a	0%	$30.00	$20.00
			b	100%		
2	$20.00	B	a	0%	$20.00	$20.00
			b	100%		
3	$20.00	C	a	100%	$20.00	$30.00
			b	0%		

In the situation depicted in Figure 4.2 the IOM employee wage index produces a counterintuitive result whereby a physician office's wage index value depends entirely on the wages of physician offices in other counties. Table 4.3 and Table 4.4 illustrate these findings. Since Physician Office *1* is the only practice in MSA *a*, the *MHW* for County *A* is \$30. Assuming that the two MSAs each comprise their own locality, the current Medicare employee wage index would assign Physician Office *1* an estimated wage level index of \$30. Physician Offices *2* and *3* both pay their workers \$20 and, the *MHW* in MSA *b* is \$20 which is one third lower than the MHW for Physician Office *1*. When applying the IOM out-commuting adjustment, however, the estimated IOM EWI values for County *A* is \$20 (i.e., W_A^* = \$30.×0% + \$20×100% = \$20) and the smoothed wage index values for Counties *B* and *C* are \$30 ($W_B^* = W_C^*$ = \$30×100% + \$20×0% = \$30). This wage reversal occurs because no workers in County *A* are employed by Physician Office *1*. A similar phenomenon occurs for Physician Office *3*. Because all workers living in County *C* work at Physician Office *1*, County *C*'s estimated wage level is set equal to the average wage at Physician Office *1* after the out-commuting adjustment is applied. Thus, IOM's EWI for Physician Office *3* depends entirely on the wage workers receive in Physician Office *1*.

4.2 Empirical Impacts of IOM's Commuting-Based Smoothing Approach

One of the aims of the smoothing adjustment is to reduce large differences in index values for providers that face similar costs markets, but are located in different GPCI payment areas. IOM claims that using commuting patterns to smooth employee wage index values improves system accuracy since commuting patterns indicate the level of "economic integration of labor markets across their geographically drawn boundaries." To test this claim, this section implements IOM's smoothing adjustment to determine if nearby physician practices have large differences in EWI and GAF values after the smoothing is applied. Although nearby counties do not necessarily face identical labor markets—see the "barrier" illustration above—on average, using distance as a proxy for the interconnectedness of labor markets can approximate whether the smoothing adjustment decreases the presence of large differences in EWI values between these nearby counties (i.e., cliffs).

The empirical evaluation below contains two components. First, Section 4.2.1 determines whether the IOM smoothing methodology effectively minimizes employee wage index cliffs. Next, Section 4.2.1 evaluates potential data sources for implementing IOM's commuting adjustment in practice. The effect of the out-commuting adjustment on county GAF values is included in Section 7, along with all other impact analyses in this report.

4.2.1 Out-Commuting Adjustment's Effect on the Presence of GAF Cliffs

To determine whether the IOM payment area definitions can reduce the size and presence of wage index cliffs, this analysis implements the broadest of IOM's proposed smoothing adjustments in practice. This analysis relies on three data files. The first data source, the 2000 Census Transportation Planning Package (CTPP), measures commuting flows between counties. This report uses the CTPP data set because of its large sample size and public availability. In its empirical implementation, IOM uses similar data.[37] Although IOM recommends using the commuting patterns of healthcare workers to implement the smoothing algorithm, the CTPP data have commuting information for all workers.[38] The second data source is the 2008 BLS OES wage data. CMS currently uses these wage data to calculate the EWI. The third and final data source is 2000 Census data, which identify the latitude and longitude of the population-weighted center of each county. Using these geographic data, this report can calculates the distance between any pair of counties.

Using these data and applying the IOM EWI methodology, Figure 4.3 illustrates the out-commuting adjustment's impact on the presence of GAF cliffs. The MSA line contains the GAF values using an MSA-based payment; the "3-tiered" line represents the GAF values calculated under IOM's recommended payment areas. The difference between the MSA and three-tiered payment areas is that the three-tiered line relies on EWI values that have been smoothed using IOM's out-commuting algorithm and the MSA payment areas do not apply this smoothing adjustment. The horizontal axis represents the distance in miles between the center of any two counties, and the vertical axis is the percentage point difference in GAF values. Thus, the figure can separately identify the change in the average size of cliffs when moving to an MSA-based payment area definition as well as the average size of cliffs after applying IOM's smoothing adjustment.

This analysis reveals that the out-commuting adjustment does reduce the size of cliffs. For counties located within 50 miles of one another in different localities, applying the smoothing algorithm to the employee wage index reduces the differences in GAF values by 0.14 percentage points (i.e., 0.0014) relative to the MSA payment area definition without smoothing. Although the magnitude of this change is small, recall that the IOM recommendation only applies the smoothing algorithm to the employee wage index, and the employee wage index constitutes only 19 percent of the total GAF value.

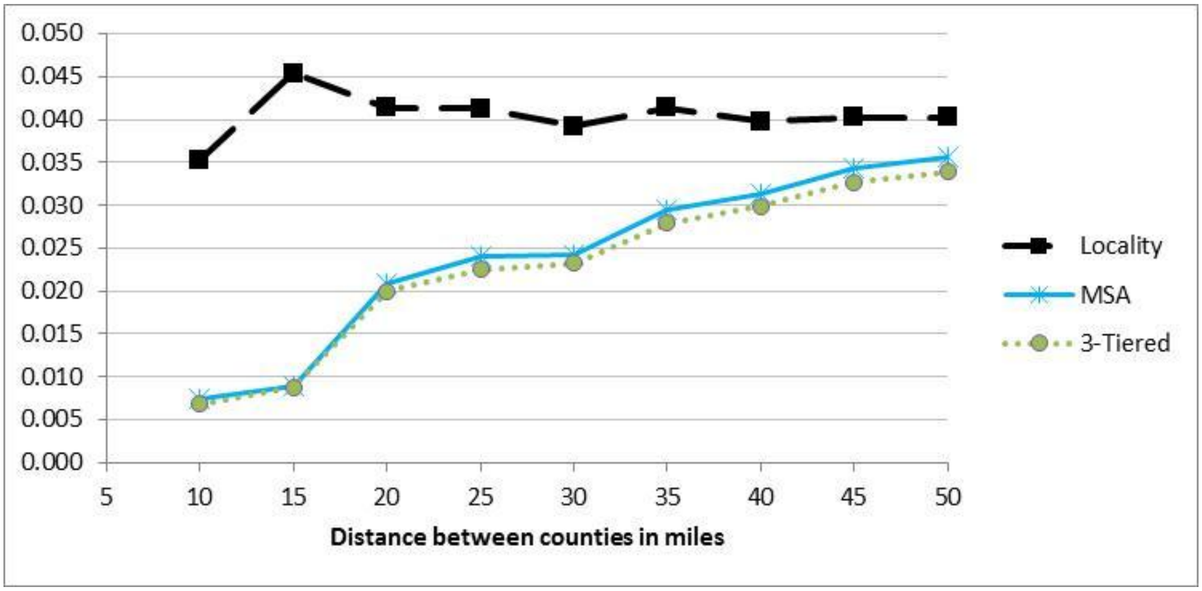
---

[37] The data are from a special tabulation of Census 2000 journey-to work data, compiled from responses to the decennial census "long-form" survey.

[38] In cases where no commuting data are available, the EWI value is set to the unsmoothed MSA EWI. Because the CTPP do not contain commuting data for Puerto Rico, EWI values for counties in Puerto Rico are proportional to the unsmoothed MHW values.

Applying the smoothing also reduces the frequency with which nearby counties have GAF differentials exceeding 5 percentage points (not shown). Whereas 12.6 percent of counties within 30 miles of one another have a GAF differential greater than 0.05 under the MSA specification, applying the smoothing algorithm to the employee wage index reduces this figure to 11.7 percent. Thus, not only does the average difference in GAF values decrease for counties located close to one another, but the share of counties with large cliffs also decreases.

Figure 4.3: Difference in County GAF Values with Out-Commuting Adjustment



4.2.2 Data Sources for Implementing IOM Commuting Adjustments

Although this analysis relies on CTPP data to measure commuting patterns, implementing IOM's smoothing adjustment in practice would require an alternative commuting data source. Because the Census long-form is no longer being collected, the Census is not a feasible source for commuting data that could be updated periodically. The ACS, however, is a potential source of commuting information. In fact, the department of transportation has released a CTPP version that uses 2006-2008 ACS data.[39] The 3-year CTPP data, however, only release commuting flow information for county pairs where the place of work and place of residence both contain at least 20,000 individuals. Due to this restriction, the 3-year CTPP data suppress a large number of commuting flow observations, particularly in rural areas. Another possibility would be for CMS to use commuting information from 5-year ACS data. The 5-year ACS contains survey responses from almost 10 million individuals and likely will have fewer

[39] http://www.fhwa.dot.gov/planning/census_issues/ctpp/data_products/acs7.cfm

data points suppressed due to the larger sample size. The 2006-2010 ACS-based CTPP, however, will not be released until 2013.[40]

An alternative would be to use commuting data collected directly from health care providers. CMS could create its own comprehensive dataset by requiring physician practices to submit data directly to CMS from their payroll records, which would report employees' counties of residence. Although these data would provide information directly on the commuting patterns of workers employed by physician practices, this approach would be administratively costly; there are hundreds of thousands of physician practices in the U.S. and nearly half of physicians work in practices with five or fewer physicians.[41] Another option would collect employee residence information from hospitals. IOM's proposed commuting-based smoothing approach in the case of physician practices is essentially the same as the approach proposed for hospitals in the HWI. Thus, CMS could collect commuting data directly from hospitals to calculate the HWI smoothing adjustment and then also could use these data for the EWI smoothing adjustment. Because commuting patterns of physician office workers and healthcare workers may differ (e.g., there exist counties with physician practices but no hospitals), adopting this approach would require the development of an empirical model to impute commuting shares for all counties with physician practices.

4.3 Measuring Wages of Workers in the Healthcare Industry

In addition to IOM's recommended changes to the employee wage index payment areas, IOM proposes using healthcare-industry wages measure earnings within each payment area. Measuring wage levels only for workers in the healthcare industry has a number of conceptual advantages and disadvantages, but as long as workers are substitutes within the broader healthcare industry (e.g., between physician offices and hospitals) but not outside the healthcare industry (e.g., between physician offices and schools), then this approach is valid. Implementing this change, however, would require CMS to gain access to confidential BLS OES data as industry-specific occupation wage estimates are only publicly available at the national level. The feasibility regarding whether CMS could access these data, however, is unclear. The following sections evaluate the conceptual pros and cons of the IOM wage measurement proposal as well as the challenges inherent in acquiring healthcare worker wage data from BLS.

4.3.1 Advantages and Disadvantages of Using Industry-Specific Wage Data

The current all-industry wage measure approach is valid when workers are viable substitutes across all industries. If the wages physicians pay workers are influenced by the wages offered to these workers by other employers both inside and outside the healthcare

[40] Based on May 7, 2012 email communication with Department of Transportation personnel.
[41] Boukus, et al. September 2009.

industry, all-industry wage estimates may be more reliable than healthcare industry wage estimates given that they provide a more complete picture of the labor market opportunities of these workers. However, all-industry worker wages may be a poor proxy for physician office worker wages in the following two cases:

- Regional variation in physician office worker wages differs from regional variation in healthcare worker wages, or
- The *level* of wages across industries varies, and the composition of industries across areas also varies.

The first case can occur when supply or demand factors cause differences in the regional variation in physician office worker wages relative to those of all other workers. On the supply side, workers may suffer a wage penalty for working in less stressful environments. For instance, nurses employed at physician practices may suffer a wage penalty relative to those employed by hospitals or other institutional providers.[42] If this wage penalty (or premium) varies geographically, using an employee wage index based on cross-industry wages will be less accurate than using wage data from physician office or healthcare industry workers alone. On the demand side, certain providers may require more-skilled workers within any occupation. For instance, physician offices may have a higher demand for more experienced or skilled registered nurses compared to home health agencies.

The second case where cross-industry wages are a poor proxy for physician office wages occurs when there is variation in wage levels across industries, and the share of healthcare industries varies nationally. If physician office workers are perfect substitutes across industries, then this issue is irrelevant because wage levels will be identical within each labor market regardless of the distribution of industries within that area. However, consider the hypothetical example presented in Table 4.5 in which nurses in MSA *1* always earn twice as much as nurses in MSA *2*. Thus, regional variation in nursing wages is constant across occupations within each industry. The wage for nurses in the offices of physicians industry, however, is 33 percent higher than the wage for nurses in the nursing home industry. Because MSA *1* has more nurses working in the offices of physicians industry than the nursing home industry, the observed cross-industry nurse wage in MSA *1* will appear 2.34 times as high as in MSA *2*. Thus, despite the fact that regional variation in nurses' wages is the same across industries, using cross-industry wage data when there is both variation in wage levels across industries and variation in industry employment across labor market create inaccuracies.

[42] Hassmiller and Cozine 2006.

Table 4.5: Example of Cross-Industry Wage Variability for Registered Nurses

	MSA 1	MSA 2	Ratio (MSA 1to MSA 2)
Offices of Physicians Wage	40.00	20.00	2.00
Nursing Home Wage	30.00	15.00	2.00
Employment in Offices of Physicians Industry	80%	25%	
Employment in Nursing Home Industry	20%	75%	
Observed Wage	38.00	16.25	2.34

In practice, the wages of occupations prominently employed by physicians vary little across the industries employing these occupations. Table 4.6 examines wages of registered nurses (RNs), licensed practical nurses (LPNs), and nursing aides across five industries using 2010 BLS OES data. Whereas the wages for hospital-based RNs are similar to the wages of RNs overall, RNs employed in physicians' offices are 4 percent higher than the national average and RNs employed in nursing care facilities earn 11 percent less than RNs nationally. On the other hand, LPNs who work in physician offices earn 9 percent less than the national average, but nursing aides that work in physician offices earn 5 percent more than the national average for nursing aides.

Table 4.6: Nursing Wages by Industry (BLS OES 2010)

Industry	Wage			Comparison vs. All-Industry Wage		
	RN	LPN	Nursing Aides	RN	LPN	Nursing Aides
Offices of Physicians	33.91	18.02	12.70	4%	-9%	5%
General Medical & Surgical Hospitals	32.99	19.35	12.87	1%	-3%	6%
Home Health Care Services	30.70	20.46	11.14	-6%	3%	-8%
Nursing Care Facilities	28.84	20.48	11.66	-11%	3%	-4%
Outpatient Care Centers	32.47	20.14	13.21	0%	1%	9%
All Industries	32.56	19.88	12.09	0%	0%	0%

To control for cases where wage levels vary across industries, CMS can implement one of three options. The first would simply measure wages within the offices of physicians industry. This option would only be feasible using cost report wage data or confidential BLS OES data. A second possibility is to use cross-industry wages but create an "industry mix adjustment" using a similar methodology to what is currently used for the HWI's occupational mix adjustment. An industry-mix adjustment, however, requires information on industry employment by area, which is not included in the publicly available data. A third option—the one IOM recommends—would measure worker wages within the healthcare industry. This approach would not control for differences in wage levels for industries within the healthcare industry but would eliminate idiosyncratic differences in regional wage variation for occupations outside the healthcare industry. One could, however, use healthcare worker wages to calculate the employee wage index and also incorporate an industry-mix adjustment within the broader healthcare industry.

In practice, however, measuring wages using healthcare-industry data rather than all-industry data is likely to have little impact on GAF values. Many of the most common occupations physician offices hire are concentrated within healthcare industries. As shown in Table 4.7, at least 85 percent of medical assistants, RNs, medical secretaries and LPNs work in the healthcare industry.[43] Occupations such as receptionists and billing clerks do have more workers employed outside the healthcare industry, but these two occupations have lower average wages ($12.87 and $15.84, respectively) than occupations concentrated in the healthcare industry, such as RNs ($31.65) or LPNs ($17.79). Because the employee wage index weights each occupation proportional to the occupation's share of the wage bill within the offices of physicians industry, low-wage occupations such as receptionists and billing clerks comprise a relatively smaller portion of the employee wage index. Further, IOM estimates that the correlation between all-industry and healthcare industry wages for occupations employed in the hospital sector is 0.994.

Table 4.7: Concentration of Physicians' Workers in Healthcare Industry (BLS OES 2010)

Occupation	Share of Physician Offices' Employment	Healthcare Employment	Total Employment	% of Occupation's Workers in Healthcare Industry	Median Hourly Wage
Medical Assistants	14%	493,210	514,970	96%	$14.19
RNs	10%	2,296,060	2,654,230	87%	$31.35
Medical Secretaries	8%	473,200	494,120	96%	$14.63
Receptionists	8%	412,080	994,750	41%	$12.87
Billing Clerks	4%	111,110	482,470	23%	$15.84
LPNs	4%	623,440	730,010	85%	$17.79

4.3.2 Advantages and Disadvantages of Using Confidential BLS OES Data

To implement wage data for workers in the healthcare industry rather than wage data for workers across all industries, CMS would require access to confidential BLS OES data. The confidential BLS OES wage data, in contrast to the publicly available file, are more detailed, include physician office-level information. The confidential data would also permit the analysis of whether occupation-specific wages vary by MSA within the offices of physician industry (or healthcare industry); as noted earlier, the publicly-available BLS data only permit the

[43] Healthcare industries are those defined as having a NAICS code beginning with 62.

measurement of regional wage variation across all industries. As a result, IOM believes that these confidential wage data represent a preferred source of information to measure regional variation in wages.

Despite these advantages, it is uncertain whether CMS could feasibly access these data. CMS must overcome two impediments to reach an agreement with BLS to use these data for payment purposes. First, there is some cost to setting up a relationship with BLS, though this cost may be small relative to the benefits of more accurate data. Second, and more important, BLS (and physicians) may be concerned about releasing the confidential data to another agency since physicians originally provided these data to BLS for reporting rather than payment purposes. Further discussions between BLS and CMS are needed to determine the feasibility for CMS to use the confidential OES data to calculate the employee wage index values using healthcare industry wage data.

5 EVALUATION OF PHYSICIAN WORK GPCI RECOMMENDATIONS

There has been much debate regarding how CMS should adjust physician work inputs for regional variation in prices. Some critics claim that physician work should not be adjusted for geographic location.[44] Many of these critics contend that "physicians providing an equivalent service for a federal program should receive the same reimbursement regardless of where they are located: 'work is work.'"[45] In contrast, others cite the theory of compensating wage differentials and argue that regional differences in the cost of living and value of amenities affect the price of labor for all occupations, including physicians. Current statute implements a compromise between these two approaches: CMS only incorporates one quarter of regional differences in physician wages into the final PW GPCI values through an adjustment known as the inclusion factor.

Rather than use a somewhat arbitrarily set 25 percent inclusion factor, IOM proposes using a regression-based empirical model to compute an appropriate PW GPCI values (Recommendation 5-3). To evaluate this recommendation, Section 5.1 presents a conceptual assessment comparing the regression-based model and the status quo for constructing wage/price indices in familiar market settings. Creating useful PW GPCI values within IOM's regression-based framework, however, depends on acquiring reliable data sources on physician compensation. Section 5.2 reviews the options for measuring physician wages using existing data sources. Next, Section 5.3 presents and evaluates several sets of empirical findings when applying a regression framework using the current-policy set of proxy occupations and a variety of data sources. IOM also proposes that CMS validate the seven current proxy occupations based on the most recent BLS OES data (Recommendation 5-2). Additional analyses described in Section 5.4 assess the extent to which regression empirical findings are sensitive to introduction of an alternative set of proxy occupations.

5.1 Discussion of Regression Approach for Predicting Physician Wages

The current construction of the PW GPCI essentially relies on price index theory familiar throughout the policy community to measure price (and wage) differences across regions and over time. A price index equals a share-weighted average of the prices of a set of commodities making up a market basket, with the shares reflecting the quantity of a commodity in the basket over its cost evaluated at a reference price. When evaluated at reference prices, the index equals one. When evaluated at another set of prices, its value shows the difference in the cost of living related to purchasing the common basket across areas or at different times.

[44] Reding September 2010.
[45] IOM 2011.

The selection of weights in a price index receives considerable attention in the literature, for it determines how to interpret the cost of living comparisons associated with the index. If, for example, one wishes to compare the cost of living for regions A and B, and one sets shares to replicate a typical basket purchased in region A, then the index reveals the difference in the cost of living faced by people living in region B who purchase the same basket; similarly, if the shares are set for a basket typically purchased in region B, then the index measures the cost of living of obtaining this basket by persons living in region B. When quantities and per unit costs in an index refer instead to the hours supplied and the wages earned by workers in different occupations, then the market basket corresponds to a particular combination of inputs, and variation in the index shows the differentials in the costs of this input combination. Calculation of such price/wage indices are commonly used to measure compensating wage differentials of the sort cited by IOM as the primary justification for geographically adjusting physician wages through GPCIs.

The regression framework proposed by IOM implicitly creates shares for an index that correspond to no interpretable market basket. Instead, the coefficients in the index reflect the degree of correlations between the price of one labor commodity and the prices of others across regions. As described in Section 3.2, the weights come from an estimated variant of a regression model taking the form

$$(5.1)\qquad \hat{y}_r = \beta_0 + \sum_{g=1}^{G} \beta_g\, x_{gr} = \beta_0 + \alpha^* \sum_{g=1}^{G} \alpha_g\, x_{gr} \equiv \beta_0 + \alpha^*\, \hat{y}_{iom}$$

where $\hat{y}_r$—the predicted value of the regression—represent the wage index for physicians in region *r* (i.e., the wage in region *r* relative to the average national wage for physicians); β_0 and β_g are regression coefficients; x_{gr} corresponds to the wage index for occupation group g in region r. The second equality in equation (5.1) redefines the coefficients as:

$$\alpha^* = \sum_{g=1}^{G} \beta_g \quad \text{and} \quad \alpha_g = \beta_g / \alpha^* .$$

IOM interprets the terms α_g as the weights within the index:

$$\hat{y}_{iom} = \sum_{g=1}^{G} \alpha_g x_{gr} .$$

The α_g coefficients, however, cannot be interpreted as shares; while their accumulative values do indeed sum to one, any individual value of α_g can be negative or greater than one. In fact, the empirical findings presented below show instances where both of these cases arise.

One must also exercise caution in adopting IOM's interpretation of the coefficient α^* in equation (5.1) as playing a role analogous to the inclusion factor used in current GPCI policy. Application of the inclusion factor in current GPCI calculations aims to dampen the responsiveness of the physician wage index across regions to changes in an occupational wage index. More specifically, with $\hat{y}_r$ designating a geographic wage index and "*IF*" denoting the inclusion factor, the PW GPCI for region *r* equals

$$GPCI_{PW,r} = 1 + IF \times \left(\hat{y}_r - E(\hat{y}_r)\right). \tag{5.2}$$

In equation (5.2), $GPCI_{PW,r} = 1$ designates that physician wage rate in region *r* is set equal to the national average rate. Computing variances (*var*) of the quantities in equation (5.2) implies

$$IF^2 = \frac{var\left(GPCI_{PW,r}\right)}{var(\hat{y}_r)} \quad , \tag{5.3}$$

which motivates interpreting *IF* as measuring the degree of damping of the variability of GPCI relative to the underlying occupational wage index. Substitution of IOM's specification (5.1) in (5.2) yields

$$GPCI_{PW,r} = 1 + IF \times \alpha^* \times \sum_{g=1}^{G} \alpha_g \left(x_{gr} - E\left(x_{gr}\right)\right) \equiv 1 + IF \times \alpha^* \times \hat{y}_{iom} \ . \tag{5.4}$$

One sees in this expression that adjustment of the coefficient α^* can indeed absorb values of *IF*. The question arises about the interpretation of coefficient α^* as a damping factor.

Viewed from a regression perspective, α^* equals a correlation coefficient times a ratio of standard deviations; the correlation coefficient relates physicians' relative regional wages y_r and IOM's composite occupation wage index $\hat{y}_{iom}$, and the ratio is the standard deviation of y_r over the standard deviation of $\hat{y}_{iom}$. Alternatively, α^* maps to the value of R-squared (R^2) associated with regressing y_r on the composite index $\hat{y}_{iom}$ through the relationship

$$(\alpha^*)^2 = R^2 \times \frac{var(y_r)}{var(\hat{y}_{iom})} \tag{5.5}$$

The value of R^2 measures the share of the variance of y_r captured by regression predicted values, which in turn measures the extent to which use of predicted values dampens variability of the original data. In the current application, the measure refers to the damping of physician regional wage variation through use of the regression wage index and not between an occupational wage index and GPCI as depicted in equation (5.3). Moreover, α^* does not even directly mirror the damping measure represented by R^2 since it is amplified or diminished by a factor depending on a ratio of variances that can be greater or less than one. The value of α^* need not be between zero and one as would be expected for a damping factor like *IF*; α^* can be negative; it can exceed one; and it can even equal zero. (We will see such instances in the empirical findings below.) Interpreting evidence that $\alpha^* = 0.25$ as supporting current GPCI policy is problematic since this parameter plays a role different from *IF*.

While difficult to interpret IOM's PW GPCI as characterizing a classic form of a wage index, the IOM approach nevertheless has a straightforward statistical interpretation as a prediction of the relative regional wages of physicians forecasted using the relative regional wages of comparable occupations. Of course, if the wages of the group of occupations deemed to be related to physicians shift uniformly across regions, then all wage indices produce the same findings, since the form of weighting does not matter. However, when non-uniform shifts occur, then the form of weighting effects the values of indices and one must select which form best capture the phenomena of interest. From an economics perspective, a regression model that relates wages in regional markets mimics a reduced form specification with coefficients that summarize the impacts of a wide range of market factors determining wages, including differences the relative supplies and demands of occupations across regions, regional variation in the number of hours various occupations work, and composition of specialists in each area. Compensating wage differentials—the principal focus of the GPCI regional adjustments—constitute only one of these factors. Notwithstanding, if one interprets the goal of PW GPCI as principally predicting regional differences in physician wages regardless of the sources of variation, then the IOM candidate offers a popular statistical candidate.

5.2 Methods and Data Sources for Measuring Physician Wages

In sharp contrast to the current PW GPCI methodology, IOM's regression-based approach requires reliable data on physician hourly wages to calculate weights for the proxy occupation wage indices. Measured geographic variation in physician compensation levels vary considerably across regions due to a number of factors unrelated to underlying wage rates. The following discussion explains these confounding factors and explores mechanisms to account for contaminating biases in estimates of regional variation in physician wages. Section 5.2.1 describes a number of techniques to control for these confounding factors, and Section 5.2.2 describes CMS's practical ability to implement these techniques using currently available data.

5.2.1 IOM Proposed Adjustments of Physician Earnings

IOM's PW GPCI adjustment requires direct measures of physician wages, but accurately computing physician wages can be complicated by a number of confounding factors. The manner in which wages are measured in the data, the complexity of services physicians provide in each region, the inclusion of profits in the compensation estimates of self-employed physicians, and the presence of outlier wage values can all cause survey wage data to inaccurately represent true wages of "typical" physicians. Table 5.1 lists prominent confounding factors that can affect area estimates of physician wages and also outlines potential adjustments proposed by researchers to compensate for these complications.

The first item in this table—measuring physician wages using annual rather than hourly compensation—is typically solved by converting annual wage date into an hourly rate based on annual hours worked. In practice, however, this solution is not always straightforward. For instance, in the ACS data, annual hours is measured using two components: weeks worked during the year and average hours worked per week. Both weeks worked and hours worked per week, however, are released to the public using categorical rather than continuous variables; thus the annul hours worked (i.e., the product of average weeks worked and average hours per week) and the hourly wage calculated using publicly-available ACS data is often imprecise. Alternatively, one can measure physician compensation per PW RVU. Since PW RVUs reflect the time—as well as the skill, effort and stress—associated with performing a given service, compensation per RVU gives a measure of the wage associated with producing a standardized RVU output unit.

Table 5.1: Proposed Adjustments for Physician Earnings Data

Confounding Factors	Adjustments to Observed Wage Data
Data measures annual compensation rather than hourly wage.	Measure hourly earnings directly.
	Measure wages as compensation per PW RVU.
Regional variation in the complexity of services provided.	Measure wages as compensation per PW RVU.
	Create specialty-mix adjustment.
Physician compensation data includes profits.	Measure earnings only for employed, salaried physicians.
Outliers affect area wage estimates.	Exclude earnings of physicians with likely outlier earnings (e.g., medical residents, part-time physicians).
	Measure median rather than mean wages in an area.

Measuring physician compensation per PW RVU also addresses the second confounding factor, regional variation in earnings due to geographic differences in the composition and complexity of services provided. Since RVUs measure the relative resource use specific procedures, using earnings per PW RVU to estimate physician wages better approximates true marginal labor productivity than earnings alone. Measuring earnings per RVU can control for regional variation not only in the volume of procedures, but also in the mix of specialties across areas as PW RVU also measure the skill required to complete a given medical service. In cases where earnings per RVU data are not available, one can substitute forms of specialty-mix adjustments. Although such adjustments cannot control for the complexity of services provided within each physician specialty, they can account for regional variation in the concentration of specialists in each across payment area. To implement a specialty-mix adjustment, one creates a separate index for each specialty based on the typical earnings level in each payment area, and physician earnings are then set equal to a weighted average of these specialty-specific indices where the weights are based on each specialty's share of the national wage bill.

The third challenge for measuring physician wages is that compensation data for self-employed physicians typically includes return-on-investment received as business owners. One option to address this issue is to limit the measure of physician earnings to salaried physicians only; the earnings of salaried physicians presumably do not include profits from ownership in the physician practice. A GAO report notes that the AMA previously recommended using this approach.[46] The drawbacks of this approach are that it: (i) reduces the number of physicians in the sample and (ii) over-represents physician specialties where large shares of physicians are paid on a salaried basis.

Finally, the presence of wage outliers can lead to wage estimates that do not represent the wages of a "typical" physician. IOM recommends two mechanisms to reduce the influence of physicians with outlier earnings on the area typical wage. IOM's first mechanism would exclude the earnings of resident physicians since their earnings are considerably lower than non-resident physicians. If resident physician wages are not excluded, the average physician earnings in areas with large teaching hospitals will be biased downwards. To calculate a wage estimate for non-resident physicians, one could either exclude medical residents from the area wage estimate or one could include medical residents as a separate specialty category in a specialty mix adjustment. When identifiers of medical resident status are not present in the data, one could restrict the sample to a subset of physicians who meet certain age thresholds with the aim of excluding the majority of residents. IOM's second proposed mechanism would rely on median wage data to reduce the influence of outliers on each area's estimated physician wage. Rather than using median wage data, CMS could measure physician compensation using use adjusted mean wage estimates, where the "adjustment" would top- and bottom-coded the wage distribution in an area. If hourly wage data are only available by area rather than for individuals within each area, the adjusted mean approach for addressing outliers would not be feasible.

5.2.2 Candidate Data Sources for Predicting Physician Wages

Some or all of these wage adjustments could be made to the four data files IOM suggests could be used to implement its regression-based PW GPCI approach. These files include wage data from: (i) BLS OES, (ii) ACS, (iii) MGMA, and (iv) AMA Physician Practices Information Survey (PPIS). Although each data source has its own advantages and disadvantages, the BLS OES and ACS files are currently the most attractive options. The PPIS has a small sample size and contains responses for less than 6,000 physicians. As a consequence, this report ignores this option due to its inability to cover many MSAs. The following discussion describes the attributes of BLS, ACS, and MGMA data sources in more detail. Table 5.2 summarizes several of the key attributes of these three data files.

---

[46] U.S. GAO 2005

Table 5.2: Data Available to Measure Physician Earnings

Definition of Physician Earnings	MGMA	ACS	BLS
Earnings/RVU	Yes	No	No
Number of Specialties Available	117	0	8
Median Earnings Available	Yes	Yes	Yes, but suppressed if median earnings >$80/hr
Can Restrict to Salaried Employees	Yes	No	Yes
Frequency of Data Collection	Annual	Continuously	Semi-annual
Benefits Data Available	Retirement Benefits Only	No	No

Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES)

BLS OES data, which CMS currently uses to measure the proxy occupation wages for the PW GPCI, offers a number of advantages over other data sources. First, the BLS OES data contain a large nationally representative random sample of workers. BLS collects wage and employment information from establishments across the United States. Second, BLS OES sample only includes data for only employees—and not the self-employed. Thus, the physicians included in the BLS data represent salaried physicians only and do not include sole practitioners or partners in unincorporated medical practices which have profits included in compensation. Third, the BLS data also contain wage and employment information for eight physician specialties.[47] BLS uses Standard Occupational Classification (SOC) physician categories. The SOC contains a more detailed breakdown of physician specialties than ACS data—which contains a single physician occupation group—but a less detailed classification system than is used in the MGMA data.

There are two problematic features, however, to keep in mind when using BLS data. The first challenge is that wage and employment information are suppressed in many MSAs in the publicly available data. The BLS does not report median wages in areas where the occupation earns more than $80 per hour (i.e., $166,400 annually). For general internists, for example, employment data are only available for 196 out of the 441 MSAs reported, and only 57 MSAs have median wage data available for these areas. Thus, the regression coefficients in the IOM model that could be estimated using median wage data would need to rely on only a relatively small, and possibly non-representative, sample of MSAs. BLS is less restrictive in its public reporting of mean wage data. Out of the 196 areas with internist employment data, BLS reports mean wage data for 184 MSAs. Consequently, using mean wages to estimate the IOM regression coefficients would yield a wider geographic coverage to calculate the PW GPCI.

[47] These eight specialties include: anesthesiologists; family and general practitioners; internists; obstetricians and gynecologists; pediatricians; physicians and surgeons (all other); psychiatrists; and surgeons.

The second problem with the BLS data concerns its representativeness of physicians' wages in an area. BLS OES only contain wage information from salaried workers. Excluding self-employed physicians from the wage estimates skews the sample towards particular physician specialties such as hospitalists and emergency medicine doctors. Table 5.3 presents a breakdown of the compensation method for the 10 largest specialties based on 2011 data from MGMA. Since the BLS restricts the sample to physicians who are only paid on a salaried basis (either salaried or salaried with incentives), only 36 percent of physicians are included in the sample. Further, even though less than a third of gastroenterologists, family practice physicians, internal medicine, and orthopedic surgeons are paid on a salaried basis, seventy four percent of hospitalists receive some form of salaried compensation.

Table 5.3: Method of Physician Compensation by Specialty (2011 MGMA Data)

Specialty	Number of Physicians Surveyed	Salaried	Salary + Incentives	Production Less Overhead	Production-Based Share	Equal Share of Payment Pool
Family Practice (w/o OB)	3634	10%	23%	38%	25%	3%
Anesthesiology	2807	19%	11%	26%	15%	29%
Internal Medicine	2427	9%	19%	38%	31%	4%
Hospitalist	2036	15%	59%	8%	14%	4%
Pediatrics: General	1850	10%	30%	29%	29%	3%
Obstetrics/Gynecology	1243	13%	23%	28%	30%	6%
Surgery: General	658	14%	18%	36%	28%	4%
Orthopedic Surgery	655	9%	14%	50%	24%	3%
Family Practice (with OB)	648	6%	19%	28%	38%	9%
Gastroenterology	549	8%	13%	37%	28%	14%
Total (Top Specialties)	16507	12%	24%	30%	24%	9%

American Community Survey (ACS)

The ACS data has three noteworthy advantages compared to the BLS data. First, although both the BLS and ACS data are large nationally representative surveys, the ACS survey is larger than the BLS. Through the ACS, Census samples nearly 3 million addresses each year resulting in nearly 2 million final observations.[48] Second, the ACS data is representative of all physicians. Whereas the BLS data is limited to salaried physicians, ACS contains both salaried and self-employed physicians. Third, ACS data permit exclusion of medical residents from this sample through imposition of restrictions on workers' age. Restricting wage estimates to physicians between the ages of 35-64 crudely removes wages for most medical residents (typically less than 35) and semi-retired physicians (typically 65 or older). Acumen received a

[48] A Compass for Understanding and Using American Community Survey Data, 2008

customized extract of physician and proxy occupation wages for workers whose age falls within this range, and all the ACS regression estimates below rely on use of this restricted age sample.

On the other hand, ACS data have three notable drawbacks. First, ACS does not break down the physician compensation data by specialty.[49] All physicians' wages are grouped into a single occupation category. Second, ACS is a household survey, and thus, worker location is based on where workers live rather than where they work.[50] Third, because ACS data contain both employed and self-employed physicians, ACS wage estimates include both compensation from labor (i.e., wages) and returns from owning a business (i.e., profit).

More formally, reported hourly earnings in ACS for self-employed workers take the form

(5.6) $$y_r = \frac{w_r + \pi_r}{\bar{w} + \bar{\pi}}$$

where w_r is the average physician wage level in region r, and π_r is the average profits per hour physicians earn in region r. The terms $\bar{w}$ and $\bar{\pi}$ correspond to the national average wage and national average profit level respectively. One can rewrite this equation as

(5.7) $$y_r = y_r^* + p_r = (w_r/\bar{w}) + p_r$$

where y_r^* measures the average physician *wage* level in region r relative to the national average (i.e., $w_r/\bar{w}$), and p_r is a term that depends on the relative profitability of physicians in the area and the share of a physician's total compensation composed of profits.[51] Using y_r as the dependent variable measuring physician compensation in a regression analysis induces biases in estimates if the wages of proxy occupations are correlated with physician profits. Ideally, the proxy occupations selected should be able to produce predicted values that measure relative wages (y_r^*) instead of relative total compensation (y_r). The term p_r captures measurement error for y_r^*. Coefficient estimates will be accurate only when proxy occupation wages are mutually uncorrelated with p_r across regions.[52] This lack of correlation is an unlikely event. The wages of nurses, for instance, constitute a large share of physician practices' labor expenses which directly influence profitability of physician offices. Consequently, use of compensation measures from ACS which includes profits can be expected to produce biased estimates of physician wages across regions.

[49] The ACS does have data for optometrists, physician assistants, chiropractors and other non-physician clinicians, but all physicians and surgeons are grouped into a single occupation category.
[50] The ACS survey does contain information on worker address. Thus, it may be feasible to identify the location where individuals work using a customized extract.
[51] $p_r = (\pi_r - w_r\bar{\pi}/\bar{w})/(\bar{\pi} - \bar{w})$
[52] As explained by Wooldridge 2002 (pages 73-74), as long as $cov(x_{gr}, p_r) = 0$ for all occupation groups g, the coefficient estimates will be unbiased. The measurement error, however, will affect the precision with which the coefficients are estimated.

Medical Group Management Association (MGMA)

Based on variables available, the MGMA data offer the possibility of implementing the majority of the IOM recommendations for adjusting physician earnings. The MGMA data provide measures of physician earnings in a variety of ways and even calculate a physician compensation to work RVU ratio. These data also classify physicians into over one hundred specialties and contain detailed information on compensation (e.g., salary, production less overhead, production-based share of practice compensation pool, equal share of practice compensation pool). MGMA even breaks down salaried compensation into "100% salaried" and "1-99% salaried with incentives" categories. Further, these data contain physician compensation data for over 40,000 physicians.

Despite the wealth of physician compensation variables available, the MGMA data do not appear reliable in practice. The MGMA response rate is under 20 percent.[53] Further, MGMA relies on a convenience sample rather than a random sample, which leads to non-representative estimates. For instance, Minnesota and Wisconsin are the only states with more than one thousand responses for the "median compensation-to-work RVU" measure.[54] New York and Florida—the third and fourth largest states in terms of population—rank 22nd and 20th, respectively, in terms of the number of responses for this statistic; each of these two large states has fewer than 300 respondents. Further, Wyoming, Alaska, and Nevada have fewer than 10 respondents for this statistic; Rhode Island, New Mexico, and Washington, DC have no observations for this variable. Non-representative samples of this type occur across a variety of MGMA's physician compensation variables. Because of the low response rates and non-representativeness of the survey, this report concludes that implementing IOM's regression-based approach with MGMA data is not feasible.

5.3 Empirical Findings Using IOM Regression Approach

This report conducts an empirical investigation of IOM's regression-based approach to address four questions:

- What are the magnitudes and signs of the regression coefficients linking proxy occupations wages to physician hourly earnings?
- Which occupation wages are statistically significantly predictors of physicians' relative wages?
- How well do the wages of proxy occupations predict physician wages?
- What is the value and interpretation of the estimated inclusion factor?

To answer these questions, the following discussion proceeds in two parts. Section 5.3.1

[53] IOM 2011.
[54] Calculated based on the responses for the top 11 physician specialties.

describes the regression methodology used to emulate the IOM approach. Next, Section 5.3.2 presents key empirical results derived from these regressions and uses these findings to explore the four questions posed above.

5.3.1 Regression Specifications

The following empirical analysis produces regression estimates exploiting two data sources:

- 2008 BLS OES mean earnings data, and
- 2005-2009 ACS median earnings data.

Although the regression specifications implemented using these data files possess a similar structure, the constructions of physician wages and proxy occupations differ across the two data sources. The discussion below first describes the regression formulation applied to the BLS OES data, and then explains adaptions implanted to use the ACS data.

Regression Specification Using BLS OES Data

The empirical application exploiting BLS OES data relies on two definitions of physician earnings to serve as the regression's dependent variable. In these specifications, the dependent variable is defined based on:

- Specialty-mix adjusted wages
- Family and general practitioner wages

Measuring a measure of mix-adjusted physician wages requires first calculating an index value for each physician specialty. The specialties include: family and general practitioners; internists, general; obstetricians and gynecologists; pediatricians; psychiatrists; and surgeons.[55] To create a single dependent variable, the analysis creates a weighted average of these specialty-specific values, where the weights equal each specialty's share of the national wage bill in the offices of physician industry. Using this specification, only 37 out of 441 MSAs have data populated for all six of the specialties considered.[56]

To attenuate the missing data problem, the second definition measures physician wages using wage data only for family and general practitioners. In this case, the dependent variable is equal to the mean family practice wage in each area divided by the RVU-weighted average

[55] Anesthesiologists had too few MSAs populated to be useful for the regression analysis. The physicians and surgeons (all other) occupation is excluded because it is composed of a wide variety of physician specialties; because regional variation in compensation for physicians in the physicians and surgeons (all other) category could be due to the composition of physician specialties within this occupation rather than wage differences, this occupation is omitted from the specialty-mix adjusted regression.

[56] The 37 figure is based on the requirement that the physician occupations and all proxy occupations have data populated for MSAs.

family practice wage across all areas included in the regression. Whereas the specialty-mix adjusted wage data only contain information for 37 MSAs, BLS OES has mean wage data on family practitioners for 203 MSAs.[57]

Once the dependent variable is defined, the set of proxy occupation wage indices that serve as covariates in the regression model are identical across the two specifications. Although these proxy occupations are largely the same as the current PW GPCI proxy occupations, several of the current policy occupations have missing wage data for at least some MSAs. The analysis narrows the proxy occupations to those with populated wage data for at least 75 percent of MSAs. Whereas the current PW GPCI approach measures median wages in each area, the regression-based approach here relies on mean wages because wage estimates are available for a greater number of MSAs in the BLS OES data.

Implementation of IOM's regression-based PW GPCI approach carries out the following five steps:

(1) *Choose the dependent variable*. The dependent variable in the BLS OES specification is either a specialty-mix adjusted physician wage or the wage only for family practice physicians.
(2) *Choose the proxy occupations.* Within the seven proxy occupation groups currently used by CMS, this step selects individual proxy occupations for which at least 75 percent of all MSAs have reported mean hourly wage information in the BLS OES data. For instance, civil, mechanical, and industrial engineers are three individual occupations chosen within the "Architecture and Engineering" occupation group, since these three individual occupations have sufficient data completeness.
(3) *Limit the regression to MSAs with populated data.* The third step limits the sample of MSAs to those for which BLS does not suppress mean physician wage data or mean occupation wage data for any of the proxy occupations. The number of MSAs included in this step varies across regression specifications depending on the dependent variable selected in step 1.
(4) *Create wage index values for all dependent and independent variables.* This step converts the wage values in steps 1 and 2 into wage index values. The index values for both physician and proxy occupations is equal to the wage in each MSA divided by the national wage, where the national average wage is weighted by the number of PW RVUs in each area.
(5) *Estimate Regression Coefficients.* The final step conducts a least squares regression using the index values created in step 4. The dependent variable is the physician

[57] The 203 figure is based on the requirement that family practice physicians and all proxy occupations have data populated for MSAs.

wage index and the independent variables are the proxy occupation wage index values plus a constant term. Each observation in the regression is weighted by the number of PW RVUs in each MSA. Weighting each area by PW RVUs places more weight on observations in MSAs where most physicians practice; further, weighting by PW RVUs follows the current CMS methodology for creating budget neutral PW GPCI values.

The above approach estimates coefficients applying weighted regression methods with weights based on regional PW RVUs. This methodology most closely corresponds to the approach applied under current policy. (All averages measuring national occupational wages use these weights as well.) An alternative specification would be to carry out estimation and variable construction without any weighting; such an analysis would relate occupational relative wages across regions with each occupation's national wage measured as the simple average of its regional wages. Appendix C compares the PW RVU-weighted estimates presented below to unweighted BLS regression results.

Regression Specification Using ACS Data

This report also emulates IOM's regression-based approach using 2005-2009 ACS data. The empirical application using ACS data differs from the BLS OES specification in five meaningful ways. First, the analysis restricts the ACS sample to workers between the ages of 35 and 64. (As noted above, this restriction largely eliminates medical resident and semi-retired physicians from the sample.) Second, whereas the BLS OES data relies on mean wages to construct physician and proxy occupation index values, the ACS data uses median wages in each area.[58] Third, the geographic unit of analysis differs across the two data files. The ACS data contains observations by Census Work Area (CWA), whereas the BLS data use MSA. Thus, the weights in the ACS regression equal the number of PW RVUs in each CWA. Fourth, whereas the BLS data include the wages of individual occupations within the seven current proxy occupation groups, the ACS regressions include wage estimates for the group as a whole. Finally, ACS measures wages according to where each worker lives rather than where they work. Thus, if physicians commute to work in an MSA that is outside the CWA where they live, that same physician will be included in different areas in the ACS compared to the BLS data.

[58] Although ACS does not report an hourly wage, the data list respondents' annual salary, weeks worked, and hours worked by year. Using these variables, this report creates an hourly wage estimate for each individual and a median wage estimate in each Census Work Area.

5.3.2 Regression Results

Corresponding to the research questions posed at the beginning of Section 5.3, four categories of statistics summarize the empirical findings of the regression analysis: (i) the range of the proxy-occupation-wage coefficients, including the number of positive and negative coefficients estimated by the regression; (ii) the number of statistically significant coefficients; (iii) the R-squared measuring a model's goodness-of-fit; and (iv) the model's estimated 'inclusion factor.' The following discussion presents these statistics along with coefficient estimates based on the BLS OES and ACS data.

Regression Results Using BLS OES Data

Table 5.4 presents the coefficient estimates and basic summary statistics computed using the BLS OES data described above. The first column lists the proxy occupation wage variable included in the regression, and the next two columns report corresponding coefficient estimates for two samples: the specialty-mix adjusted physician wage sample and the family/general practitioner sample. (Following conventional notation, the star superscripts signify the level of significance of the coefficient estimates.) The bottom panel of the table presents additional summary statistics describing the regression estimation.

As seen in the table, the magnitudes of the regression coefficients are much larger for the multi-specialty regression than the family practice regression. Inspecting the multi-specialty results, the coefficients vary from 0.764 to -0.780, with coefficients for "network systems and data communications analysts," "network and computer systems administrators," and "paralegals and legal assistants" all above 0.5, and coefficients for computer systems analysts and computers support specialist are both below -0.5. Seven occupations have positive coefficients and twelve occupations have negative coefficients. Inspecting the family practice results, the range of the coefficients is much smaller falling between 0.197 and -0.283. "Mechanical engineers, computer software support specialists" have coefficients above 0.150, and "arts, design, entertainment, sports and media and civil engineers" have coefficients below -0.150. The occupations with large coefficients in the specialty mix regression are not the same ones with large coefficient magnitudes in the family practice regression. For instance, "commuter support specialists" has a large negative coefficient in the specialty mix specification, but a large positive coefficient in the family practice regression.

Table 5.4: Regression Results for PW GPCI Using Current Proxy Occupations

Variable	Multi-Specialty	Family Practice
Intercept	1.001 **	1.168 ***
Civil engineers	0.203	-0.282 **
Mechanical engineers	-0.060	0.197
Industrial engineers	0.413	-0.063
Computer support specialists	-0.534	0.192
Network and computer systems administrators	0.661	0.088
Computer systems analysts	-0.780 *	0.059
Computer programmers	-0.193	0.064
Computer software engineers, applications	-0.177	0.110
Network systems & data communications analysts	0.764 **	0.010
Lawyers	-0.345 *	-0.140
Educational, vocational, and school counselors	-0.238	-0.068
Social and human service assistants	0.361 *	-0.065
Child, family, and school social workers	0.340 **	0.028
Paralegals and legal assistants	0.568	0.061
Medical and public health social workers	-0.123	-0.034
Education, training, and library occupations	-0.235	-0.065
Registered nurses	-0.063	0.021
Pharmacists	-0.215	0.002
Arts, design, entertainment, sports, & media	-0.346 *	-0.283 ***

Stars indicate level of significance: * = reject zero at 10%; ** = reject zero at 5%; and *** = reject zero at 1%.

Statistic	Multi-Specialty	Family Practice
Number of MSAs	37	202
R-Squared	0.652	0.194
Estimated "inclusion factor"	-0.001	-0.168

Relatively few estimates of regression coefficients are statistically significant in either specification. In the specialty mix adjustment regression, only 6 of the 19 proxy occupation coefficients are statistically significantly different from zero at the 10 percent level. At the 5 percent level, only two proxy occupation coefficients are statistically significant. Similarly, in the family practice specification only two proxy occupations have statistically significant coefficients at the 5 percent level. The only occupation that is statistically significantly different from zero in both regressions is the arts and entertainment regression; in both specifications, however, its coefficient is negative.

Inspection of the bottom panel of Table 5.4 reveals that the multi-specialty regression produces an improved goodness-of-fit compared to the family practice regression. According to the R^2 statistic, predicted values from the multi-specialty regression explain about 65 percent of the variation in physician wages, whereas predicted values from the family practice regression explain less than 20 percent of the variation. The specialty mix regression is estimated on a much smaller sample of MSA due to suppressed values in the BLS OES data; the specialty mix adjusted regression relies on data for 37 MSA and the family practice regression uses data for 202 MSAs. Since the 37 MSAs are mostly large urban areas, their similarity would typically produce a higher goodness of fit than a diverse set of MSA. Using family practice wages as the dependent variable, but restricting the MSAs to the same 37 included in multi-specialty regression produces an R^2 value of 0.598 (results not shown). Thus, the differences in the goodness of fit statistics in the two specifications can fully be explained by sample composition.

As discussed in Section 5.1, IOM's proposed "inclusion factor" does not directly correspond to the damping factor currently used in GPCI calculations, but instead represents a standard deviation weighted correlation coefficient between physician wages and an IOM-style composite proxy occupation wage index ($\hat{y}_{iom}$). As seen in the bottom panel of Table 5.4, the estimated inclusion factor in the multi-specialty specification is approximately zero—meaning that the composite proxy occupation composite wage index is uncorrelated with physician wages—and the estimated factor in the family practice specification is negative—implying that a composite proxy occupation wage index is inversely correlated with physician wages. In other words, in MSAs where physician wages are above average, the composite proxy occupation wage index is likely to be below average.

One source for the zero or negative correlation between physician wages and the composite proxy occupation wage index ($\hat{y}_{iom}$) arises due to the fact that large metropolitan areas with high wages for proxy occupations often have relatively low physician wages. Table 5.5 displays wage data for family practitioners in the 2,963 counties with mean wage data available in the BLS OES. The rural-urban continuum code of 1 represents counties in metro areas with a population of 1 million or more. Not only are wages for physicians in the largest urban areas below the national average, but these physicians also are the lowest among all rural-urban continuum codes. Findings are similar for internists, OB/GYN, pediatricians, and surgeons.[59]

[59] The only case where physicians in rural-urban continuum code 1 are not among the codes with the lowest earnings is psychiatrists. For psychiatrists, RVU-weighted earning in Rural-urban continuum code 1 are $74.26, which is above the earnings of psychiatrists in rural-urban continuum code 3 ($61.16) and 4 ($68.71), but below the national average wage of $74.86.

Table 5.5: Family and General Practitioner Wages by Rural-Urban Status (BLS OES 2008)

Metro/ Non-metro	Rural-Urban Code	Counties	RVUs	Avg. Wage	RVU-Wgt Avg. Wage
All	*All*	*2,963*	*1,074,916,810*	*$78.51*	*$76.05*
Metro	1	413	605,831,851	$77.03	$74.06
	2	312	241,593,037	$80.52	$78.75
	3	221	85,759,123	$79.48	$79.15
Non-metro, Urban	4	214	51,465,236	$77.94	$77.83
	5	104	27,687,295	$77.48	$77.57
	6	598	33,021,002	$78.74	$78.68
	7	441	24,212,551	$78.07	$78.12
Non-metro, Rural	8	229	2,437,331	$78.89	$79.22
	9	431	2,909,384	$78.45	$80.08

To highlight this finding, consider the case of four large U.S. MSAs: Los Angeles, New York, Chicago and Philadelphia. Although these cities have high wages for most proxy occupations, the mean physician wages reported by the 2008 BLS OES are much lower than smaller cities in their same state. The average wage of family practice physicians in the Los Angeles-Long Beach-Glendale, CA MSA is only $59.28, compared to average wages of over $80 in smaller cities such as Stockton, Bakersfield, and Fresno, California. The wages of family practice physicians in the New York-White Plains-Wayne, NY-NJ MSA ($67.81) are 17 percent lower than the wages of family practitioners in the Buffalo-Niagara Falls, NY MSA ($82.15). Further, the MSA containing the city of Chicago has lower average physician earnings than physicians in the "Rest of Illinois" residual area; physician earnings in Philadelphia are also lower than Pennsylvania’s non-metro areas.

There are a number of reasons why average physician earnings in large cities are no larger than physician earnings in non-metropolitan areas. First, large cities tend to have large teaching hospitals. Since large teaching hospitals rely on medical resident labor more than other facilities, the average wages in these areas may be deflated by the large number of medical residents. Further, studies using the Community Tracking Study’s (CTS) Physician Survey also conclude that the wages of urban physicians are not statistically significantly different from the wages of physicians in rural area.[60] Second, physicians as a group may value the amenities in cities more than in other less densely-populated areas. If this is the case, physicians may be willing to accept a lower wage to work in densely-populated urban areas. Third, in large cities increased provider competition may drive down earnings. Because of the increased supply of

[60] Reschovsky and Staiti 2005.

physicians in concentrated metropolitan areas, consumers and insurers may be more price sensitive than would be the case in rural areas and may be able to drive down the prices of physician services.

Regression Results Using ACS Data

The discussion below compares the regression results using ACS data against those described above using BLS data. The ACS data may offer improved estimates because it includes all physicians (and does not exclude self-employed physicians as BLS does). Further, the ACS data used is restricted to workers between the ages of 35 and 64, largely eliminating physician wage outliers due to their status of being medical residents or semi-retired. The two major drawbacks of the ACS data are that one cannot control for physician specialty and measured physician wages include compensation from both wages and profits.

Table 5.6 presents the regression estimates based on the ACS data. The estimates display a range similar to those exhibited by the BLS family practice specification. The largest positive coefficient (pharmacists) is 0.211 and the largest negative coefficient (Art and Entertainment) is -0.137. Three of the regression coefficients on occupational wages are positive and four are negative. In contrast to the BLS results, a majority of the regression coefficients are statistically significant. Four of the seven occupation groups have a coefficient that is statistically significantly different from zero; three coefficients are positive and one is negative.

Despite the fact that the ACS regression produces a majority of coefficient estimates that are statistically significantly different from zero, the ACS regression model does not fit the physician wage data as well as the regression model using BLS data. Whereas the R^2 for the BLS multi-specialty regression is 0.654 and is 0.194 for the BLS family practice regression, the R^2 for the ACS regression is merely 0.076.

Table 5.6: Regression Results for PW GPCI Using 2005-2009 ACS

Variable	Coefficient
Intercept	0.825***
Engineering	0.201***
Science and Math	-0.111
Social Science	0.160***
Education	-0.055
Registered Nurses	-0.095
Pharmacists	0.211***
Art and Entertainment	-0.137***

Stars indicate level of significance: * = reject zero at 10%; ** = reject zero at 5%; and *** = reject zero at 1%.

Statistic	
Number of Census Work Areas	509
R-Squared	0.076
Estimated "inclusion factor"	0.175

In contrast to the BLS regression, the ACS results produce a positive estimated IOM inclusion factor of 0.175. This figure indicates a positive correlation coefficient between physician wages and an IOM-style composite proxy occupation wage index ($\hat{y}_{iom}$).

A number of factors could explain these results. First, removing medical residents by restricting the age range to physicians 35-64 may be responsible for the larger number of statistically significant regression coefficients. If restricting the data to this age range reduces outlier wage values caused by areas with high concentrations of medical residents, the regression may be able to detect a relationship more precisely between physician wages and proxy occupations. In addition, the proxy occupation wage indices may be measured more precisely. The number of survey observations used to calculate the proxy occupation wage index is larger, not only because the ACS has a larger sample size, but also because the ACS regression specification uses occupation groups instead of individual occupations. Differences in the goodness-of-fit results may be driven by increased diversity of payment areas. The ACS data has far more CWAs (509) than the number of MSAs in either of the BLS regressions (37 and 202 respectively) and the physician wage estimates in sparsely-populated CWAs may be imprecise. Further, regional variation in the composition of physician specialties in ACS could also cause its R^2 to be small. Finally, profits are a part of physician earnings in ACS, and this contamination may induce idiosyncratically variation across regions.

5.4 Estimates Using Alternative Proxy Occupations

To evaluate IOM's recommendation to re-evaluate the proxy occupations used in the PW GPCI index, the following analysis uses three criteria for selecting an alternative set of occupations. These criteria restrict proxy occupations to:

- Non-physician occupations where more than 80 percent of workers have a bachelor's degree;
- Occupations that constitute more than 5 percent of physician offices' non-physician labor expenses; and
- Occupations without wage data in a sufficient number of payment areas.

Although IOM does not explicitly state which proxy occupations should be used, this report surmises that these three above restrictions represent reasonable criteria by which CMS could select proxy occupations beyond those currently incorporated in calculating PW GPCI.

Just as the current proxy occupations in the PW GPCI aim to represent "highly educated, professional employee categories," the first criterion aims to identify educated workers in a more systematic fashion. For instance, the current PW GPCI relies on wages from the "Arts, Design, Entertainment, Sports, and Media" occupation group (SOC 27-0000). Although this occupation includes professional occupations such as writers/authors, news analysts, and reporters, it also includes occupations with a lower average education levels—such as film and video editors, radio operators, and broadcast technicians; these workers' wages are less likely to be correlated with physician wages. By limiting the occupation to those where a large share of workers have a bachelor's degree, the proxy occupations are more likely to be correlated with underlying physician wages. For the empirical application, this analysis defines these occupations as those where at least 80 percent of workers had a bachelor's degree. Because the BLS OES data do not have person-level education information, the analysis requires that at least 80 percent of the occupation's workers in the 2005-2009 ACS PUMS had achieved a bachelor's degree.[61]

To avoid selecting occupations whose wage could affect physician earnings indirectly, the second criterion excludes proxy occupations that comprise a large share of physician office labor costs. In the current PW GPCI specification, these occupations are not explicitly omitted. Registered nurses, for instance, are included as a proxy occupation and registered nurses make up about 20 percent of the offices of physician industry's non-physician labor cost.[62] Because nurses' wages directly affect physician profits, the assumption that the wages of registered nurses are uncorrelated with physician earnings is likely violated, particularly if self-employed workers are included in the physician wage estimates. To avoid potential contamination, the list of

[61] This report uses the Census 2000 Special EEO File Crosswalk to map BLS SOC codes to Census occupation codes.
[62] Calculations use May 2008 BLS OES data within the Offices of Physicians Industry (NAICS 621100).

alternative proxy occupations excludes those that make up more than 5 percent of the non-physician wage. The empirical application below determines the non-physician wage bill for each occupation using data from the May 2008 BLS OES within the offices of physicians industry.[63]

Finally, the analysis limits proxy occupations to those that have wage data in a sufficient number of areas. The exact wage data requirements depend on the variables used to measure the earnings. For the purposes of the empirical work relying on BLS OES data, the analysis requires the occupation to have populated wages for areas that make up at least 50 percent of nationwide RVUs. For instance, the BLS OES data only contained wage information for the biochemists and biophysicists occupation in 9 percent of counties. These counties contained only 35 percent of the PW RVUs nationwide, and thus this occupation is excluded from consideration. BLS does not contain regional wage data for most teaching occupations as it considers them seasonal workers; thus teachers are also not included as a proxy occupation.

Thirty one occupations meet these three criteria. Appendix D contains a complete list of these alternative proxy occupations. Although this report uses all 31 occupations to create PW GPCI values under CMS's current index-based methodology (see Section 7 for these results), the proxy occupations included in the regression analysis requires the occupations also are required to have populated wage data for all MSAs in which there is a direct measures of physician wages (i.e., the dependent variable). Imposing this available data restriction decreases the number of proxy occupations in the alternative occupation regression specification to nine.

Table 5.7 displays the regression results using the BLS OES data for the expanded set of proxy occupations under the two physician wage specifications discussed in Table 5.4; Table 5.8 presents summary statistics comparing the regression results under the original and alternative proxy occupation specifications. Whereas the regression model using the original occupations contains 19 proxy occupations, the model using the alternative definition only includes 9 independent variables.

Implementing a regression-based PW GPCI methodology using the alternative occupations produces qualitatively similar results as the original set of proxy occupations. In both specifications, about half of the coefficients are positive. Fewer coefficients are statistically significant in the alternative specification. Just as is the case under the original occupation regression specification, the estimated IOM "inclusion factor" under the alternative occupation model is negative. Applying IOM's regression-based framework with the alternative set of proxy occupations also does not improve the models' goodness-of-fit. This analysis does not

[63] The Offices of Physicians industry is NAICS code 621100.

answer whether any other set of proxy occupations could offer a better model fit, only that the alternative proxy occupations selected using the three criteria above fails to do so.

Table 5.7: Regression Results for PW GPCI Using Alternative Occupations

Variable	Multi-Specialty	Family Practice
Intercept	1.001 ***	1.145 ***
Pharmacists	0.033	0.104
Lawyers	-0.308 *	-0.081
Librarians	0.108	-0.169
Physical therapists	-0.188	0.091
Civil engineers	0.269	-0.134
Speech-language pathologists	0.134	0.081
Engineering managers	-0.263	-0.179 *
Occupational therapists	-0.072	-0.071
Computer software engineers, applications	0.211	0.213 **

Stars indicate level of significance: * = reject zero at 10%; ** = reject zero at 5% level; and *** = reject zero at 1% level.

Statistic	Multi-Specialty	Family Practice
Number of MSA	36	237
R-Squared	0.351	0.107
Estimated "Inclusion" Factor	-0.078	-0.145

Table 5.8: Comparison of PW GPCI Regressions Using Original and Alternative Occupations

Specification	R-Squared	Inclusion Factor	Positive Coefficients	Statistically Significant Coefficients				Number of Coefficients*
				1%	5%	10%	Total	
Specialty Mix								
Original	0.652	-0.001	7	0	2	4	6	19
Alternative	0.351	-0.077	5	0	0	1	1	9
Family/General Practitioner								
Original	0.194	-0.168	11	1	1	0	2	19
Alternative	0.107	-0.145	4	0	1	1	2	9

* The "Number of Coefficients" column counts all coefficients except for the coefficient on the intercept term.

6 EVALUATION OF GPCI OFFICE RENT RECOMMENDATIONS

After identifying significant limitations in several sources of commercial rent data, IOM proposes that CMS develop a new source of data to measure geographic variation in the price of commercial office rent per square foot. The new data source would replace the current the ACS residential rent data that CMS currently uses to calculate the office rent index. Although IOM cites a number of reasons why using commercial rent data to calculate the office rent index is preferable to residential rent data, IOM does not, however, indicate where the data should come from or how they should be collected. As IOM did not indicate a unique source of rent data to use for the PE GPCI office rent index, this section not only assesses the feasibility of developing a new source of commercial rent data, but also evaluates existing sources of commercial and residential rent data.

The following discussion proceeds in three parts. Section 6.1 evaluates the feasibility of collecting a new source of commercial rent data. In the cases where a collecting commercial rent data is prohibitively expensive and duplicative of existing efforts, Section 6.2 examines a variety of commercial rent data sources. The section examines a number of sources not included in the IOM report, such as commercial rent data from the CoStar Group and LoopNet. In the event that no commercial rent data source is determined to be acceptable to construct the office rent index, Section 6.3 revisits sources of residential rent data CMS that could use as proxies measures of regional variation in the price of commercial rental properties.

6.1 Creating a New Data Source for Commercial Rents

Although collecting rent data from physicians could improve the accuracy of the office rent index, there are four significant drawbacks to developing and collecting a new source of commercial rent data. First, the large number of physicians in the U.S. would make collecting a new source of office rent data administratively costly. According to the 2010 Statistical Abstract of the U.S. Census Bureau, there are approximately 661,400 physicians and surgeons in the U.S. Surveying all these physicians on a recurring basis would be an expensive endeavor. Collecting rent data from a representative sample of physicians—rather than the full population—is more cost-effective, but ensuring that the sample size is large enough to have sufficiently precise office rent estimates in each payment area would still involve considerable expenses. Second, physician response rates are typically low. One study found that average physician response rates for a large sample survey (> 1,000 observations) were only 52 percent.[64] This response rate does not compare favorably to those of large nationally representative surveys such as the ACS (household response rate over 95 percent) or BLS OES (establishment response rate over 75

[64] Cummings, Savitz, and Konrad. 2001.

percent).[65] Third, using office rent data collected directly from physicians creates circularity within the index. Physicians who rent medical office space will have an incentive to inflate reported rents to increase GPCI values in their area. To prevent this circularity problem, CMS could audit the data, but this option would add additional administrative costs to the data collection process. Fourth, developing and collected a new source of commercial office rent might partially replicate existing data. As described below, CoStar collects rental information for a variety of commercial properties including physician offices; MGMA samples physicians on their typical office rent cost. The next section evaluates the commercial rent data sources available from CoStar, MGMA and other sources.

6.2 Existing Commercial Rent Data Sources

Rather than collecting a new source of commercial rent data, CMS could also rely on existing sources of commercial rent data to calculate the office rent index. Commercial rent data sources that may be considered for use in the office rent index ideally should meet six criteria. First, the rent data should measure rents only for commercial office space rather than residential or industrial properties. Second, the rent data source should have a large sample size. A data source with a small sample size will produce imprecise estimates of physicians' costs to rent office space, particularly for sparsely populated rural areas. Third, the rent data should be national in scope, with coverage of both metropolitan and non-metropolitan areas. Fourth, the rent data source should measure property quality in order to account for geographic variation in the quality of office building.[66] Fifth, the rent data should measure the price of office space based on per square foot *gross* rents. If the office rent index is constructed from data that cannot be adjusted for the type of lease, the index will underestimate rents in areas where the lessee typically pays a large share of overhead costs (e.g., utilities, insurance, taxes, maintenance).[67]

---

[65] See ACS Response Rates Data (http://www.census.gov/acs/www/methodology/response_rates_data/) and 2011 BLS OES Technical Notes (http://www.bls.gov/oes/current/oes_tec.htm).

[66] The Building Owners and Managers Association (BOMA) classifies office space into three categories: Class A, Class B, and Class C. For more information on BOMA classifications, see: http://www.boma.org/resources/classifications/Pages/default.aspx. If the PE GPCI office rent index is constructed from data unadjusted for the quality of the building, the index may reward areas that have more high-quality buildings. On the other hand, constructing the office rent index from data adjusted for building quality may not take into account that the supply of buildings in an area may be skewed to a particular quality level; for example, an area may only contain Class A office buildings, offering physicians no opportunities to rent Class B or C facilities.

[67] Adjusting for the lease type can control for regional differences with respect to whether the tenant or landlord pays for overhead costs. Commercial leases can be classified into three types based on the share of overhead included in the rent: Triple Net (NNN), Modified Gross (MG), and Full Service (FS). In addition to the base rent, NNN leases require tenants to separately pay expenses of the property, including taxes, insurance, maintenance, electric, janitorial, etc., separately. MG leases require tenants to pay a portion of these overhead expenses in addition to the base rent. These typically include electrical and janitorial expenses. In FS leases, the landlord covers all rental expenses (e.g., base rent, utilities, janitorial, taxes, etc.). If the PE GPCI office rent index is constructed from data unadjusted for the type of lease, the index would measure gross rents for FS contracts, but net rents for NNN leases.

Sixth, the rent data should be publicly available so that office rent index calculations are transparent for physicians and inexpensive for CMS to acquire on a recurring basis. With these six criteria in mind, this report evaluates rental data from CoStar, LoopNet, Reis Inc., the MGMA, and selected federal agencies.

6.2.1 CoStar Group

CoStar offers detailed national commercial rent data for over 2.8 million commercial properties covering over 10 billion square feet of space. CoStar provides both asking rent and the leasing rent per square foot for each of these properties and claims that it can provide these data for every county in the nation. Property owners post listings for free on the CoStar database; this policy contributes to the size and scope of CoStar's database because alternative commercial office rent databases charge a fee to list property.[68] CoStar independently verifies the price of every property listing posted. To do this, CoStar employs more than 1,000 researchers that canvass markets, collect, and verify property details. CoStar's database tracks many property types, including office, retail, industrial, commercial, land, multi-family, mixed-use properties, and hospitality, and CoStar updates its data on a monthly basis. CoStar also offers a proprietary algorithm that adjusts rents for lease type.[69] Many government agencies, including the General Services Administration (GSA), the Federal Deposit Insurance Corporation (FDIC), and the Federal Reserve, already use CoStar's database.[70]

For the purposes of the office rent index, the CoStar data can be limited to commercial "office" buildings. This restriction eliminates rental property types such as industrial space and undeveloped land. For this subset of commercial listings, CoStar has a large number of listings including nontrivial number listings in rural areas. For instance, CoStar has commercial rent data for rural areas like Montana (1,000 office listings) and Wyoming (295 office listings). In addition, CoStar allows users to further narrow the office property type to a secondary "Medical Office" property type. Although an office rent index using medical office rent data could more effectively measure physicians' cost to rent office space, the sample size in certain rural areas is too small to create precise estimates.

Though CoStar offers a comprehensive commercial office rent data source, this option does have some drawbacks. First, because CoStar's data are proprietary, CMS would need to secure an agreement with CoStar before publishing any data or indices using CoStar's rent data. Second, access to CoStar's data is expensive. CoStar requires, at the minimum, a year-long subscription and estimated that it would cost approximately $40,000 per year for CMS to access CoStar's national database.

---

68 For example, LoopNet (http://www.loopnet.com/).
69 Communicated to Acumen through a CoStar representative.
70 Based on email communication with CoStar representatives.

6.2.2 LoopNet

Like CoStar, LoopNet offers commercial rent data on a national level. Specifically, LoopNet offers data for approximately 800,000 properties covering over 6.7 billion square feet of space. For each of these properties, LoopNet provides data on asking rents per square foot. LoopNet's database tracks a variety of property types, including office, retail, industrial, multifamily, and land. Like the CoStar data, LoopNet's data can be limited to commercial "office" buildings. While LoopNet's rent data are available free of charge, property owners are charged a fee by LoopNet to post listings on the LoopNet website.

However, there are two disadvantages to using LoopNet data. First, LoopNet offers less than one third the amount of data that CoStar offers (i.e., CoStar has 2.8 million commercial properties, while LoopNet has 800,000 commercial properties). As a result, LoopNet's listings have smaller sample sizes in largely rural states like Montana (158 office listings) and Wyoming (17 office listings). Second, rents on LoopNet are typically not verified by an independent source. Whereas CoStar employs market researchers that verify property details, LoopNet listings are maintained by the brokers who list the commercial properties on LoopNet. As a result, LoopNet's commercial office rent data may not reflect true rental rates because brokers may forget to update their property listings.

6.2.3 Reis, Inc.

Reis, Inc. also maintains a comprehensive national commercial property dataset that provides price per square foot for office, retail, and industrial properties. Unlike the CoStar data, however, the Reis data has a limited scope, providing commercial rent rates for properties larger than 10,000 square feet for 169 metropolitan areas, and office rent estimates for only 82 metropolitan areas. In addition, Reis only tracks approximately 40% of the inventory in each of these markets. As a result, the Reis data have a smaller sample size, are not geographically complete, and do not reflect market prices in both metropolitan and nonmetropolitan areas.

6.2.4 Medical Group Management Association (MGMA)

Although MGMA is the only group that collects rental information specifically for physician practices, the MGMA rental information is a poor source for calculating the office rent index. Specifically, these data have three noteworthy drawbacks. First, although MGMA invites about 11,000 medical practices to complete each of the two surveys it conducts (cost survey and compensation survey), the response rates for these surveys are typically below 20 percent. Thus, the survey has a limited sample size which primarily captures information for physician practices operating in metropolitan areas. Second, MGMA has uneven response rates across regions. For example, almost twice as many Colorado practices completed the surveys compared to California; the survey includes more provider responses from Minnesota (ranked 21st in population) than any other state. Finally, as described in Section 5, there are few observations for many small states.

6.2.5 Federal Agencies: USPS and GSA

Commercial rent information is also collected by various federal agencies. For example, the United States Postal Service (USPS) collects data on commercial properties leased or owned by the USPS, and the General Services Administration (GSA) gathers data on commercial rent for federal and government properties. Specifically, the USPS offers data on commercial properties leased or owned by USPS, while GSA offers commercial rents for federal buildings in particular. Because these sources only collect data on federal and government properties, however, they may not be representative of regional variation in rental costs relevant for physicians. While the USPS data have the advantage of being available free of charge to the public, the GSA data only makes limited data publicly available.

6.2.6 Overview: Comparison of Commercial Rent Data Sources

After utilizing the six rent data criteria discussed at the beginning of Section 6.2, this report finds that the comprehensive data from the CoStar Group is the most viable option for calculating the office rent index. The CoStar data offer several distinctive strengths. The CoStar data offer commercial office rents, which measure rents for properties that physicians would rent. The CoStar data also have the largest sample size of the six commercial data sources evaluated and are geographically diverse, representing both metropolitan areas and rural areas nationally. Further, the CoStar data track property quality and type of lease.

One can see these advantages when CoStar is compared to other commercial rent data sources. Although LoopNet offers similar nationwide data on office rents, LoopNet's data are less accurate than CoStar's data due to LoopNet's data collection and data verification methods. LoopNet's data also suffer from a smaller sample size; as a result, LoopNet's data may not accurately represent physicians' costs to rent office space. While Reis also maintains a comprehensive national commercial property dataset, it is more limited in scope than CoStar data as it provides rents for only certain metropolitan areas. Finally, while the MGMA, USPS, and GSA offer commercial rent data as well, these organizations only collect data on specific subsets of commercial properties. As a result, these data may not accurately represent physicians' costs to rent office space. Table 6.1 summarizes the similarities and differences among the six commercial rent datasets according to the six criteria listed at the beginning of this subsection.

Table 6.1: Comparison of Data Sources for Office Rent

	CoStar	LoopNet	REIS, Inc.	MGMA	GSA	USPS
Property Data Available	Commercial asking rents and leasing rents for office, retail, industrial, commercial land, multi-family, mixed-use, and hospitality properties.	Commercial asking rents and leasing rents for retail, office, apartment, and land investments.	Commercial rent rates for properties larger than 10,000 sq. ft., at zip code, county, and MSA levels.	Data on building and occupancy, reported as percentage of total revenue.	Commercial rent for federal and government properties only.	Commercial properties leased or owned by USPS.
Sample Size	Over 2.8 million commercial properties with over 10 billion sq. ft. of space.	Approximately 600,000 commercial properties with over 6.7 billion sq. ft. of space.	169 MSAs total; REIS, Inc. samples 40% of each region each quarter.	1,871 practices.	All federal government buildings.	25,300+ leased properties, 8,500+ owned properties.
Data Scope	Individual properties for both metropolitan and non-metropolitan areas.	Individual properties for both metropolitan and some non-metropolitan areas.	Metropolitan areas.	Non-metropolitan (<50,000): 21.15% Metropolitan (50,000-250,000): 29.29% Metropolitan (250,000-1,000,000): 32.67% Metropolitan (>1,000,000): 16.88%.	Federal government buildings only; does not reflect traditional market behavior or all geographic regions.	All USPS properties (leased and owned).
Data on Property Quality	Data on BOMA classification.	Some data on BOMA classification.	Data on BOMA classification.	No.	No.	No.
Data on Type of Lease	Data on NNN, MG, and FS rents.	Some Data on NNN, MG, and FS rents.	Data on NNN, MG, and FS rents.	No.	No.	No.
Availability to Public	Yes, for a fee.	Yes, free of charge.	Yes, for a fee.	Yes, for a fee.	Limited data are available.	Yes, free of charge.

6.3 Residential Rent Data Sources

While the PE GPCI office rent index currently relies on residential rental data as a proxy for physicians' costs for commercial office space, this approach may not always be valid. Using residential rent data as a proxy for commercial rent data is a valid approach when residential rents are proportional to commercial rents. This proportionality typically would occur in flexible markets when people can use land for both residential and commercial purposes. Geographic variation in residential and commercial rents, however, need not always be proportional. Markets can have different levels of demand for residential and commercial properties; alternatively, zoning laws may restrict supply differently for commercial and residential properties. Both demand and supply factors could cause geographic variation in residential rents to fail to be proportional to regional variation in commercial rents. As a result, residential rent data sources have been criticized as not reflecting commercial space or actual cost differences in metropolitan and nonmetropolitan areas.

Despite these drawbacks, existing sources of residential rent data do offer a number of practical advantages over commercial rent data sources. First, large nationally representative residential rent data sets exist. Second, acquiring these data is simple and occurs at little cost. Third, residential rent data is publicly available, thus enhancing the transparency of the office wage index. Since residential rend data do have some practical advantages over existing commercial rent data sources, this section examines threes sources of residential rent data: the ACS, U.S. Department of Housing and Urban Development (HUD) Fair Market Rents (FMR) data, and U.S. Department of Defense (DOD) Basic Allowance for Housing data (BAH).

6.3.1 American Community Survey

CMS currently uses ACS rent data in its office rent index calculation. The ACS is one of the largest nationally representative surveys of household rents in the United States. As described in earlier sections, the U.S. Census Bureau sends this survey to approximately 3 million addresses per year and recent response rates are above 97 percent.[71] The ACS reports rental information for residences with 0, 1, 2, 3, 4, or 5+ bedrooms at the county level; this rental information also includes utilities cost.[72] Acumen obtained a customized extract of the ACS data with gross rents by bedroom size from the U.S. Census Bureau to use in the PE GPCI office rent methodology.

[71] ACS Response Rates are available here: http://www.census.gov/acs/www/methodology/response_rates_data/
[72] Utilities cannot be analyzed separately since some individuals' monthly rent covers the cost of utilities. Thus, the ACS data can only accurately measure gross (i.e., including utilities) rents rather than net rents. In the ACS survey, individuals report whether electricity, gas, water/sewer, and oil/coal/kerosene/wood costs (i.e., questions 11a, 11b, 11c, and 11d on the survey) charges were included in their rent and – if not – they report what their utility cost was during the past 12 months. See: http://www.census.gov/acs/www/Downloads/questionnaires/2012/Quest12.pdf.

For FY 2012, CMS is using 2006-2008 ACS residential rent data to create the office rent index. Although the Census currently offers 1-year, 3-year, and 5-year releases of its ACS data, CMS adopted the 3-year dataset for CY 2012 because it has a larger sample size than the 1-year ACS release and relies less on outdated data compared to the 5-year release. While the 1-year dataset is the most current dataset, it nevertheless has a smaller sample size than the 3-year dataset as it reports rental rates only for counties with populations of 65,000+. On the other hand, although the 5-year dataset has a larger sample size and reports rent information for all counties, the 5-year data are less current than the 3-year data. For example, creating the GPCI office rent index using 5-year 2006-2010 estimates would include somewhat outdated data from 2006-2007, whereas the 3-year data relies only on the more recent 2008-2010 estimates. For the 3-year dataset, ACS does not report rental rates for any bedroom size for counties with fewer than 20,000 individuals. To impute rents for counties with less than 20,000 people without rental data, CMS estimates its rent based on the weighted average rents of counties with more than 20,000 people in the same MSA. CMS chose to use the most recent 3-year ACS rent data to calculate the PE GPCI office rent index going forward.[73]

6.3.2 HUD Fair Market Rents

Although HUD also relies on ACS rents as part of its 2012 Fair Market Rent (FMR) calculations, it includes several adjustments for inflation and other factors.[74] To calculate the 2012 FMR, HUD uses the 2005-2009 5-year ACS estimates of 2-bedroom adjusted standard quality rents. However, in areas where the 2005-2009 5-year ACS estimates are smaller than the reported margin of error, then the state non-metro estimate of 2-bedroom adjusted standard quality rent is used instead. Because HUD's mandate requires HUD to measure rents for recent movers, HUD modifies the 5-year ACS estimates with a recent mover bonus factor[75] and a Consumer Price Index (CPI) adjustment by region.[76] Finally, estimates are trended for 1.25 years with a trending factor of 3 percent per year to arrive at the FY 2012 2-bedroom FMRs.

---

[73] Acumen has analyzed using 5-year ACS rental data from 2005-2009 and found that using the 5-year data instead of the 3-year data from the ACS has a small impact on localities' office rent index values; only about one in ten localities experience a change in its office rent index value by more than one percentage point.

[74] The primary use of the HUD FMR is to determine payment standards for HUD programs such as Section 8 contracts and the Housing Choice Voucher program.

[75] HUD calculates the recent mover bonus factor by comparing a 2009 1-year adjusted recent mover 2-bedroom rent to the 5-year adjusted standard quality rent for the same area. If the 1-year data are statistically different than the 5-year data, HUD calculates the recent mover bonus factor as the ratio of the 1-year to the 5-year rents; if the 1-year data are not statistically different than the 5-year data, HUD applies a recent mover bonus factor of 1 to the 5-year data. HUD also adjusts the 5-year ACS estimates using CPI rent and utilities price indices. For the full methodology, see: http://www.huduser.org/portal/datasets/fmr/fmr2012f/FY2012_FR_Preamble.pdf.

[76] Specifically, HUD uses the annual change in the "Rent of Primary Residence" and "Fuels and Utilities" indices from the "Housing" component of the CPI-U to calculate the relevant June 2009 to December 2010 Update Factors for FMRs. For the full methodology, see: http://www.huduser.org/portal/datasets/fmr/fmrs/docsys.html&data=fmr12.

HUD then compares these values against the state minimum rent, and any area for which the preliminary FMR falls below this value has its FMR raised to the level of the state minimum.

Prior to CY 2012, CMS used HUD FMR data to calculate the PE GPCI office rent index; however, CMS switched to using the ACS data for several reasons. First, using ACS data for the office rent index follows the spirit of Section 3012 of the Affordable Care Act (ACA), which mandates that CMS explore the use of ACS data for portions of the PE GPCI. Second, prior to 2012, the HUD FMR estimates by geographic areas were based partially on 2000 Census long form data.[77] Since these data are over 10 years old, CMS recommended moving to the more recent ACS data, which the Census Bureau now uses to replace the long-form Census questionnaire. Third, because HUD often re-bases its methodology, an office rent index constructed with HUD FMR data would be more volatile over time. By calculating an office rent index directly from ACS data rather than HUD FMR data, CMS would retain more control over the methodology used to calculate residential rents in each region. Fourth, the HUD FMR methodology described above is more complex and harder for providers to replicate compared to the rent data from the ACS.

6.3.3 Basic Allowance for Housing

Another source of residential rent information is the DOD BAH. When government quarters are not provided to uniformed service members, DOD uses the BAH to estimate additional payments to these individuals based on housing costs in local civilian housing markets within the United States. The DOD uses a contractor to collect the nation-wide housing cost data that are used to compute the BAH. Although the DOD collects rent data independently to compute the BAH, the DOD uses ACS rent data to estimate utilities cost in its BAH estimates. DOD calculates BAH rents for every region in the United States, even though some regions may have no military population. The BAH localities aggregate individual ZIP Codes into groups called Military Housing Areas (MHAs). An MHA includes rental markets surrounding a duty station or metropolitan area, and there are approximately 350 geographic MHAs in the U.S.

BAH data has two important disadvantages. First, the sample may not be representative of physician office locations. DOD focuses its survey in areas consisting of neighborhoods where the top 80% of service members live.[78] The sample also excludes "undesirable" neighborhoods as determined by local military housing offices. Second, the sample size of the BAH is much smaller than the ACS data.

[77] "Final Fair Market Rents for Fiscal Year 2011 for the Housing Choice Voucher Program and Moderate Rehabilitation Single Room Occupancy Program" *Federal Register* 75 (4 October 2010): 61254-61319. http://edocket.access.gpo.gov/2010/pdf/2010-24465.pdf.

[78] For more information, see Military Compensation FAQs: http://militarypay.defense.gov/pay/bah/03_faqs.html

7 EMPIRICAL IMPACTS OF IOM RECOMMENDATIONS

Although this report has evaluated the relative merits of each IOM proposal, it has yet to determine whether the proposals are quantitatively meaningful in the sense that they induce non-trivial changes in locality or county GAF values. To assess the quantitative impacts of the IOM recommendations, the following empirical analysis compares GAF values assuming adoption of each IOM proposals against the status quo. Statistics used to measure the magnitude of GAF value changes include the average absolute change in GAF value, the number of counties that experienced an increase or decrease in GAF value, and the distribution of percentage point GAF changes. This section calculates these statistics for IOM recommendations related to:

- Redefining payment areas;
- Implementing a regression-based PW GPCI methodology; and
- Modifying the proxy occupations used to calculate the PW GPCI.

The following discussion investigates the quantitative impacts of these proposals on GAF values, with the successive subsections below considering a proposal in the order they appear above.

7.1 Effects of Redefining Payment Areas

IOM's three-tiered payment area definition would redefine GPCI payment areas in two ways. First, IOM proposes applying a commuting-based smoothing adjustment to the employee wage index as discussed in Section 4. Second, rather than relying on the existing locality-based system, IOM proposes using MSAs to define payment areas when measuring regional variation in physician wages, office rents, purchased services, and malpractice premiums. Although using MSA-based payment areas is not an explicit IOM recommendation—Recommendation 2-1 proposes the use of MSAs only for labor market definitions—the IOM report does state that the IOM Committee recommends "a set of areas that are consistent with hospital markets, increasing the number of physician payment areas from the current 89 to 441 (the number of hospital payment areas)."[79] The 441 figure directly corresponds to the number of MSA/rest-of-state areas reported in the BLS OES data. The third tier of IOM's recommended payment areas assigns a national payment area for the equipment and supplies index.

To evaluate these IOM payment area recommendations, the following analysis will examine these two modifications both separately and combined. Table 7.1 presents an overview of these three specifications. The columns of this table list the regions entertained as candidates for calculating geographic adjustments of payments to physicians. Its rows list the individual GPCI components incorporated in the PFS. An "*X*" in a row indicates the payment area suggested by IOM to compute the GPCI component indicated in the corresponding row. The

[79] IOM, 2-19.

equipment, supplies, and other index is excluded from the table as all specifications rely on a national payment area (i.e., this component index is not geographically adjusted).

Table 7.1: Summary of IOM's Payment Area Recommendations

GPCI Component Indices	Labor Market Smoothing Adjustment			MSA-Based Payment Areas			IOM Three-Tiered Payment Areas		
	County	*MSA*	*Locality*	*County*	*MSA*	*Locality*	*County*	*MSA*	*Locality*
Physician Work GPCI			**X**		**X**			**X**	
Employee Wage Index	**X**				**X**		**X**		
Purchased Services Index			**X**		**X**			**X**	
Office Rent Index			**X**		**X**			**X**	
Malpractice Insurance GPCI			**X**		**X**			**X**	

The following three sections evaluate each specification in turn. Section 7.1.1 conducts an impact analysis narrowly for IOM's smoothing algorithm. Section 7.1.2 conducts a similar analysis for MSA-based payment areas, and also compares the MSA-based payment areas with other proposed payment area definitions such as the county and statewide tier definitions. Finally, 7.1.3 analyzes the impact of instituting all IOM payment area recommendations.

7.1.1 Implementing the Out-Commuting Based Smoothing Adjustment

To identify the effect of smoothing, this section compares the IOM employee wage index definition against an MSA-based employee wage index without smoothing. Although one could compare the IOM employee wage index values against the current EWI values using the locality-based payment areas, that analysis would confound two affects—switching to a smaller MSA-based payment area and applying the smoothing adjustment. Thus, to narrowly identify the effect of smoothing, all results in this section are compared to a baseline where all component indices are defined at the MSA-level. To implement the smoothing adjustment for the employee wage index, this section relies on the same commuting data and methodology described in Section 4.

Table 7.2 displays the results of this analysis using the county as the unit of observation. This table and all others in the section are structured similarly, with a left panel (with three columns) and a right panel (with two columns). The left panel displays the distribution of counties across various ranges of possible differences in GAF values. The right panel displays various summary statistics of the distribution of GAF differences. For example, the first row of the right panel reports the average GAF difference across all counties, whereas the second row of the right panel reports the average of the absolute value of GAF differences across all counties.

Implementing IOM's smoothing adjustment has a moderate effect on employee wage index values. As shown in Table 7.2, for 73 percent of counties the employee wage index changes by less than 1 percentage point as a result of smoothing. Further, over 99.8 percent of counties experience changes of less than 5 percentage points. The average absolute change is 0.009 as a result of smoothing, and the median change is 0.001.

Since IOM only recommends applying the smoothing adjustment to the employee wage index, one can also compare PE GPCI and GAF values under IOM's three-tiered payment areas (i.e., with EWI smoothing) against MSA-based payment area definition for all component indices. Since the smoothing adjustment is only applied to the employee wage index, the impact of IOM's employee wage index out-commuting adjustment is attenuated at the PE GPCI and GAF levels. As seen in Table 7.3, in the case of the revised practice expense GPCI, nearly 91 percent of counties experience changes of less than 1 percentage point as a result of smoothing, and 99.9 percent experience changes of less than 5 percentage points. The average absolute change is 0.004 as a result of smoothing, and the median change is 0.001. As expected, the changes due to smoothing the employee wage index are further attenuated at the GAF level. As seen in Table 7.4, 98.7 percent of counties experience changes of less than 1 percentage point in their GAF value as a result of smoothing, and all experience changes of less than 5 percentage points. The average absolute change is 0.002 as a result of smoothing, and the median change is 0.000. Overall, these results show that the out-commuting-based smoothing adjustment does not have a dramatic effect on index values for the case of MSA-based payment areas.

Table 7.2: Difference in Employee Wage Index With and Without Smoothing

Employee Wage Index Difference	# of Counties	% of Counties
All	**3,223**	**100.0**
> 0.10	5	0.2
0.05 to 0.10	52	1.6
0.01 to 0.05	648	20.1
0.00 to 0.01	**1,215**	**37.7**
-0.01 to 0.00	**1,131**	**35.1**
-0.05 to -0.01	170	5.3
-0.10 to -0.05	2	0.1
< -0.10	0	0.0

Percentile	Employee Wage Index Difference
Mean	0.005
Abs. Mean	0.009
Min	-0.097
P10	-0.006
P25	-0.002
P50 (Median)	**0.001**
P75	0.008
P90	0.021
Max	0.134

Table 7.3: Difference in PE GPCI With and Without Smoothing

PE GPCI Difference	# of Counties	% of Counties
All	**3,223**	**100.0**
> 0.10	0	0.0
0.05 to 0.10	2	0.1
0.01 to 0.05	261	8.1
0.00 to 0.01	**1,657**	**51.4**
-0.01 to 0.00	**1,273**	**39.5**
-0.05 to -0.01	30	0.9
-0.10 to -0.05	0	0.0
< -0.10	0	0.0

Percentile	PE GPCI Difference
Mean	0.002
Abs. Mean	0.004
Min	-0.039
P10	-0.002
P25	-0.001
P50 (Median)	**0.001**
P75	0.003
P90	0.009
Max	0.054

Table 7.4: Difference in GAF With vs. Without Smoothing

PE GPCI Difference	# of Counties	% of Counties
All	**3,223**	**100.0**
> 0.10	0	0.0
0.05 to 0.10	0	0.0
0.01 to 0.05	40	1.2
0.00 to 0.01	**1,880**	**58.3**
-0.01 to 0.00	**1,301**	**40.4**
-0.05 to -0.01	2	0.1
-0.10 to -0.05	0	0.0
< -0.10	0	0.0

Percentile	PE GPCI Difference
Mean	0.001
Abs. Mean	0.002
Min	-0.018
P10	-0.001
P25	0.000
P50 (Median)	**0.000**
P75	0.002
P90	0.004
Max	0.026

7.1.2 Payment Area Definitions Based on MSAs

Switching from the status quo definition of payment areas (i.e., Medicare localities) to MSA-based payment areas creates large changes in county GAF values. Unlike the analysis above, no smoothing is applied to the EWI under the MSA-based specification. Further, whereas the analysis above used MSA-based payment areas as the baseline comparison group, in this section the comparison group is county GAF values under the current locality-based system. As shown in Table 7.5, the typical county experiences a change in its GAF value of between 2 and 3 percentage points when the MSA-based payment area definition is implemented. Further, about 13 percent of counties experience a gain or loss in their GAF value of less than one percentage point when the MSA payment area definition is used, while approximately 8 percent of counties experience a change in their GAF values greater than 5 percentage points.

One can also consider how the MSA-based payment areas would affect GAF values in comparison to other proposed candidate payment area definitions, such as counties or statewide tiers. Implementing a county-based payment area definition (without any smoothing) produces a similar change in GAF values as the MSA-based payment areas. Table 7.6 compares county GAF values when payment areas are defined by counties against county GAF values where payment areas are defined by localities. The table shows that about 14 percent of counties experience a gain or loss in their GAF value of less than one percentage point when the county-based payment area definition is used. Approximately 10 percent of counties experience a change in their GAF values greater than 5 percentage points. These results are similar to the MSA-based results since many of the GPCI component indices rely on data that only varies at the MSA level (e.g., BLS OES wage data).

Changing from the status quo to statewide tiers, on the other hand, produces the smallest change in GAFs among these three candidate payment area definitions. The statewide tier payment area, presented in the July 2007 proposed rule as "Option 3," combines counties into tiers within each state based on each county's GAF value.[80] Table 7.7 compares this option against the locality-based status quo. This table shows that about 18 percent of counties experience a gain or loss in their GAF value of less than one percentage point when the statewide payment area definition is used. In fact, the average (un-weighted) absolute change in a county's GAF value when changing from the status quo to statewide tiers is 0.026; on the other hand, the average absolute change in a county's GAF value when changing from the status quo to either counties or MSAs is 0.030.

[80] Appendix B contains a more detailed definition of statewide tiers.

Table 7.5: Difference in GAF when Switching to MSAs (Locality Baseline)

GAF Difference	# of Counties	% of Counties
All	**3,223**	**100.0**
> 0.10	18	0.6
0.05 to 0.10	67	2.1
0.01 to 0.05	374	11.6
0.00 to 0.01	**190**	**5.9**
-0.01 to 0.00	**241**	**7.5**
-0.05 to -0.01	2,154	66.8
-0.10 to -0.05	173	5.4
< -0.10	6	0.2

Percentile	GAF Difference
Mean	-0.019
Abs. Mean	0.030
Min	-0.142
P10	-0.044
P25	-0.036
P50 (Median)	**-0.027**
P75	-0.005
P90	0.019
Max	0.199

Table 7.6: Difference in GAF when Switching to Counties (Locality Baseline)

GAF Difference	# of Counties	% of Counties
All	**3,223**	**100.0**
> 0.10	12	0.4
0.05 to 0.10	51	1.6
0.01 to 0.05	342	10.6
0.00 to 0.01	**199**	**6.2**
-0.01 to 0.00	**236**	**7.3**
-0.05 to -0.01	2,129	66.1
-0.10 to -0.05	252	7.8
< -0.10	2	0.1

Percentile	GAF Difference
Mean	-0.022
Abs. Mean	0.030
Min	-0.125
P10	-0.047
P25	-0.038
P50 (Median)	**-0.028**
P75	-0.008
P90	0.016
Max	0.155

Table 7.7: Difference in GAF when Switching to Statewide Tiers (Locality Baseline)

GAF Difference	# of Counties	% of Counties
All	**3,223**	**100.0**
> 0.10	17	0.5
0.05 to 0.10	51	1.6
0.01 to 0.05	337	10.5
0.00 to 0.01	**393**	**12.2**
-0.01 to 0.00	**170**	**5.3**
-0.05 to -0.01	2,054	63.7
-0.10 to -0.05	200	6.2
< -0.10	1	0.0

Percentile	GAF Difference
Mean	-0.017
Abs. Mean	0.026
Min	-0.121
P10	-0.045
P25	-0.031
P50 (Median)	**-0.021**
P75	-0.002
P90	0.018
Max	0.155

The impact analysis also shows that most counties experience a decrease in their GAF values under any of the three candidate payment area definitions. When changing from the status quo to MSAs more than 80 percent of counties experience a decrease in their GAF values. The results for the county and statewide tier definitions are 81 and 75 percent respectively. The composition of the statewide localities and rest of state localities is the source of this result. Whereas many metropolitan areas are currently located within a "rest of state" locality or statewide locality (, the county, MSA, and statewide tier definitions separate these urban areas into distinct payment areas. For instance, using the MSA-based definition, the residual "rest of state" areas would be comprised entirely of non-urban areas and, thus, would experience a decrease the GAF values in these areas. Because more counties (but not necessarily more RVUs) are located in rural areas, most counties experience a decrease in GAF when moving away from the locality definition.

Changing from the status quo to a county, MSA, or statewide tier payment area definition increases GAF values for urban counties and decreases them for rural ones. Table 7.8 presents a breakdown of changes in GAFs for urban and rural counties. The table uses the U.S. Department of Agriculture's 2003 Rural-Urban Continuum Codes[81] to classify counties. Counties with a code of 1 are located in metro areas of 1 million people or more, counties with a code of 2 are located in metro areas with 250,000 to 1 million people, and counties with a code of 3 are located in metro areas with fewer than 250,000 people. Counties with a code of 4, 5, 6, or 7 are non-metro urban areas, and counties with a code of 8 or 9 are completely rural areas with fewer than 2,500 people. The USDA does not classify counties in Puerto Rico or the Virgin Islands, and thus the change in GAF for these counties is reported as a separate line. Counties in large metropolitan areas see an increase in the GAF of between 1.8 to 2.5 percentage points depending on the payment area specification, but counties in rural areas experience a decrease in their GAF values of between 2.8 and 3.5 percentage points depending on whether the county is adjacent to a metro area and which payment specification is used. Urban non-metro areas, on average, also experience a decrease in their GAF values regardless of whether they have more than 20,000 people (codes 4 and 5) or fewer than 20,000 people (codes 6 and 7).

[81] Available on the USDA Economic Research Service website: http://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx

Table 7.8: Change in GAF by Urban-Rural Continuum Code

Metro/ Non-metro	Rural-Urban Continuum Code	Number of Counties	Payment Area Definition		
			County	MSA	Statewide Tier
Metro Area	1	414	0.018	0.025	0.019
	2	325	-0.003	0.002	-0.003
	3	351	-0.013	-0.011	-0.012
Non-metro, Urban	4	218	-0.035	-0.036	-0.027
	5	105	-0.030	-0.031	-0.022
	6	609	-0.038	-0.035	-0.031
	7	450	-0.035	-0.032	-0.028
Non-metro, Rural	8	235	-0.035	-0.033	-0.028
	9	435	-0.033	-0.032	-0.028
Puerto Rico/ Virgin Is.	Puerto Rico/ Virgin Is.	81	0.008	0.010	0.010

7.1.3 Implementing IOM Three-Tiered Payment Area Recommendations

Implementing all changes proposed in IOM's three-tiered payment area definitions produces similar changes in GAF values as switching to an MSA-based payment area without any smoothing. Implementing all IOM recommendations creates: (i) a county-based payment area for the employee wage index, (ii) an MSA-based payment areas to measure physician wages, office rent, purchased services and malpractice premiums; and (iii) a national payment area for equipment and supplies. The difference between IOM's three-tiered payment areas and the MSA-based payment areas described above is the application of the smoothing adjustment to the EWI. Table 7.9 compares the IOM three-tiered payment area against the current locality-based payment areas and reveals that when switching the three-tiered payment areas from the baseline of Medicare localities, most counties experience a decrease in their GAF values; more than 80 percent experience a decrease and less than 20 percent experience an increase. The largest decrease in a GAF value is 0.141. The largest increase is 0.195. Most changes in GAF values, however, are more moderate; 92 percent of counties experience a change (in either direction) of less than 0.05. The average change in GAF values across all counties is -0.018, and the median change is -0.025. Of the less than 10 percent of counties that experience a change exceeding 0.05, in over two thirds of cases (i.e., about 68 percent) this involves a decrease in the GAF value. Overall, these results are similar to those from the MSA impact analysis (without smoothing) presented above.

Table 7.9: Difference in GAF: IOM Three-Tiered Payment Area vs. Medicare Locality

GAF Difference	# of Counties	% of Counties
All	**3,223**	**100.0**
> 0.10	18	0.6
0.05 to 0.10	64	2.0
0.01 to 0.05	373	11.6
0.00 to 0.01	**185**	**5.7**
-0.01 to 0.00	**273**	**8.5**
-0.05 to -0.01	2,134	66.2
-0.10 to -0.05	171	5.3
< -0.10	5	0.2

Percentile	GAF Difference
Mean	-0.018
Abs. Mean	0.028
Min	-0.141
P10	-0.043
P25	-0.034
P50 (Median)	**-0.025**
P75	-0.005
P90	0.020
Max	0.195

7.2 Effects of Regression-Based Methodology for Calculating PW GPCI

Using the PW GPCI regression-based specification described in Section 5.3.1, this impact analysis finds a relatively large change in PW GPCI and GAF values after the regression-based approach is implemented. Table 7.10 and Table 7.11 display the impact of adopting the regression-based approach, where physician earnings are measured as a weighted average of six specialties. The table compares this specification against the current approach where the PW GPCI is calculated as a weighted average of proxy occupation wages, where the weights are each occupation’s share of the national wage bill. As shown in these tables, the average change in a locality’s PW GPCI is over 8 percentage points. Further, only 7.9 percent of localities experience a change in their PW GPCI values of less than 1 percentage point, whereas over a third of localities experience a change in their PW GPCI values of more than 10 percentage points. The changes in GAF values are large as well. The average locality would experience a change in its GAF of over 4 percentage points using the regression-based approach, and only about 15 percent of localities would experience a change in their GAF of less than 1 percentage point.

Table 7.10: Impact Analysis: Specialty-Mix Regression (PW GPCI)

Work GPCI Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	14	15.7
0.05 to 0.10	17	19.1
0.01 to 0.05	10	11.2
0.00 to 0.01	**4**	**4.5**
-0.01 to 0.00	**3**	**3.4**
-0.05 to -0.01	16	18.0
-0.10 to -0.05	9	10.1
< -0.10	16	18.0

Percentile	Work GPCI Difference
Mean	0.006
Abs. Mean	0.086
Min	-0.220
P10	-0.136
P25	-0.079
P50 (Median)	**0.000**
P75	0.079
P90	0.157
Max	0.413

Table 7.11: Impact Analysis: Specialty-Mix Regression (GAF)

GAF Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	4	4.5
0.05 to 0.10	10	11.2
0.01 to 0.05	23	25.8
0.00 to 0.01	**8**	**9.0**
-0.01 to 0.00	**5**	**5.6**
-0.05 to -0.01	23	25.8
-0.10 to -0.05	15	16.9
< -0.10	1	1.1

Percentile	GAF Difference
Mean	0.003
Abs. Mean	0.042
Min	-0.106
P10	-0.066
P25	-0.038
P50 (Median)	**0.000**
P75	0.038
P90	0.076
Max	0.199

Changes in PW GPCI and GAF values for the family-practice regression specification are large, but somewhat smaller in magnitude than the specialty-mix specification. Table 7.12 and Table 7.13 display these results. Whereas the average change in locality PW GPCI values is 8.6 percentage points for the specialty-mix specification, for the family-practice specification the change is only 6 percentage points. The corresponding value for the change in GAF is 2.9 percentage points. Despite the smaller changes, only 11 percent of localities would experience a change in their PW GPCI of less than 1 percentage point, and only one in four localities would experience a change in their GAF values of less than 1 percentage point under the family-practice regression-based specification.

Table 7.12: Impact Analysis: Family Practice Regression (PW GPCI)

Work GPCI Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	6	6.7
0.05 to 0.10	22	24.7
0.01 to 0.05	20	22.5
0.00 to 0.01	**8**	**9.0**
-0.01 to 0.00	**2**	**2.2**
-0.05 to -0.01	16	18.0
-0.10 to -0.05	6	6.7
< -0.10	9	10.1

Percentile	Work GPCI Difference
Mean	0.008
Abs. Mean	0.060
Min	-0.188
P10	-0.122
P25	-0.027
P50 (Median)	**0.013**
P75	0.065
P90	0.091
Max	0.172

Table 7.13: Impact Analysis: Family Practice Regression (GAF)

GAF Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	0	0.0
0.05 to 0.10	6	6.7
0.01 to 0.05	35	39.3
0.00 to 0.01	**15**	**16.9**
-0.01 to 0.00	**7**	**7.9**
-0.05 to -0.01	17	19.1
-0.10 to -0.05	9	10.1
< -0.10	0	0.0

Percentile	GAF Difference
Mean	0.004
Abs. Mean	0.029
Min	-0.091
P10	-0.059
P25	-0.013
P50 (Median)	**0.007**
P75	0.032
P90	0.044
Max	0.083

7.3 Effects Using an Alternative Set of PW GPCI Proxy Occupations

Whereas the analysis above examines changes in the PW GPCI from implementing a regression-based methodology, this section calculate the impact of using an alternative set of proxy occupations. As described in Section 5, these alternative proxy occupations have a large share of workers with a college education but these occupations are also ones that make up a small share of physician offices' labor expenses. The following sections examine the use of an alternative set of proxy occupations under the current CMS methodology and under IOM's proposed regression based framework. Section 7.3.1 presents an impact analysis to illustrate the changes in locality PW GPCI and GAF values that occur as a result of applying these alternative definitions in the current PW GPCI methodology. Section 7.3.2 describes the combined impact of implementing IOM's regression based framework with the alternative set of proxy occupations.

7.3.1 Impacts of Alternative Occupations Using Current Methodology

To determine the impact of applying this alternative occupation definition, this report follows the same PW GPCI methodology used for the CY 2012 GPCI, but changes the proxy occupations based on the specifications described above. Specifically, the proxy occupations are weighted using the share of the occupation's wage bill nationally and the inclusion factor is set to 25 percent. This analysis uses May 2008 BLS OES data to measure wages and employment.

Because there exists broad overlap between alternative proxy occupations and the occupations currently used in the PW GPCI methodology, using alternative proxy occupations to calculate the PW GPCI results in small changes to the PW GPCI and the GAF. Table 7.14 and Table 7.15 display the impact analysis of using alternative proxy occupations to compute the PW GPCI. The average change in the locality's PW GPCI value is less than 1 percentage point, and no localities experience a change in their PW GPCI of more than 5 percentage points. Further, about two-thirds of localities experience a change in their PW GPCI of less than 1 percentage point. The changes in the GAF values are even smaller. The average change in the locality's GAF is 0.4 percentage points. Further, no localities experience a change their GAF values by more than 1.1 percentage points.

Table 7.14: Alternative Proxy Occupations Impact Analysis (PW GPCI)

Work GPCI Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	0	0.0
0.05 to 0.10	0	0.0
0.01 to 0.05	15	16.9
0.00 to 0.01	**34**	**38.2**
-0.01 to 0.00	**26**	**29.2**
-0.05 to -0.01	14	15.7
-0.10 to -0.05	0	0.0
< -0.10	0	0.0

Percentile	Work GPCI Difference
Mean	0.000
Abs. Mean	0.008
Min	-0.022
P10	-0.013
P25	-0.005
P50 (Median)	**0.001**
P75	0.008
P90	0.012
Max	0.024

Table 7.15: Alternative Proxy Occupations Impact Analysis (GAF)

GAF Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	0	0.0
0.05 to 0.10	0	0.0
0.01 to 0.05	1	1.1
0.00 to 0.01	**48**	**53.9**
-0.01 to 0.00	**38**	**42.7**
-0.05 to -0.01	2	2.2
-0.10 to -0.05	0	0.0
< -0.10	0	0.0

Percentile	GAF Difference
Mean	0.000
Abs. Mean	0.004
Min	-0.010
P10	-0.006
P25	-0.003
P50 (Median)	**0.000**
P75	0.004
P90	0.006
Max	0.011

7.3.2 Impacts of Alternative Occupations Using Regression-Based Methodology

When introducing the alternative proxy occupations to calculate the PW GPCI within the regression-based framework, on the other hand, there are large changes in the PW GPCI values. Table 7.16 and Table 7.17 contain the PW GPCI and GAF impact tables for the specialty-mix specifications. In this specification, the average locality experiences a change in its PW GPCI of 5.2 percentage points and a change in its GAF value of 2.5 percentage points. Although these changes are much larger than what would occur were CMS to substitute the alternative occupations for the current seven proxy occupation groups within the current methodology, relying on these alternative occupations creates smaller changes to GPCI and GAF values than the regression-based approach using the current list of occupations. Table 7.18 and Table 7.19 present the analogous tables for the family practice regression specification. The average change in the PW GPCI and GAF values under the family practice specification are nearly identical to the specialty mix specification. The family practice specification, however, has a slightly lower share of localities whose GAF value changes by less than 1 percentage point (21 percent) compared to the specialty mix specification (26 percent).

Table 7.16: Alternative Occupation Impact Analysis: Specialty-Mix Regression (PW GPCI)

Work GPCI Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	5	5.6
0.05 to 0.10	14	15.7
0.01 to 0.05	25	28.1
0.00 to 0.01	4	4.5
-0.01 to 0.00	6	6.7
-0.05 to -0.01	16	18.0
-0.10 to -0.05	12	13.5
< -0.10	7	7.9

Percentile	Work GPCI Difference
Mean	0.000
Abs. Mean	0.052
Min	-0.164
P10	-0.092
P25	-0.038
P50 (Median)	0.009
P75	0.045
P90	0.072
Max	0.174

Table 7.17: Alternative Occupation Impact Analysis: Specialty-Mix Regression (GAF)

GAF Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	0	0.0
0.05 to 0.10	2	2.2
0.01 to 0.05	35	39.3
0.00 to 0.01	11	12.4
-0.01 to 0.00	12	13.5
-0.05 to -0.01	23	25.8
-0.10 to -0.05	6	6.7
< -0.10	0	0.0

Percentile	GAF Difference
Mean	0.000
Abs. Mean	0.025
Min	-0.079
P10	-0.045
P25	-0.018
P50 (Median)	0.004
P75	0.022
P90	0.035
Max	0.084

Table 7.18: Alternative Occupation Impact Analysis: FP Regression (PW GPCI)

Work GPCI Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	1	1.1
0.05 to 0.10	21	23.6
0.01 to 0.05	19	21.3
0.00 to 0.01	**8**	**9.0**
-0.01 to 0.00	**5**	**5.6**
-0.05 to -0.01	15	16.9
-0.10 to -0.05	12	13.5
< -0.10	8	9.0

Percentile	Work GPCI Difference
Mean	-0.002
Abs. Mean	0.052
Min	-0.203
P10	-0.095
P25	-0.038
P50 (Median)	**0.004**
P75	0.049
P90	0.080
Max	0.104

Table 7.19: Alternative Occupation Impact Analysis: FP Regression (GAF)

GAF Difference	# of Localities	% of Localities
All	**89**	**100.0**
> 0.10	0	0.0
0.05 to 0.10	1	1.1
0.01 to 0.05	37	41.6
0.00 to 0.01	**11**	**12.4**
-0.01 to 0.00	**8**	**9.0**
-0.05 to -0.01	24	27.0
-0.10 to -0.05	8	9.0
< -0.10	0	0.0

Percentile	GAF Difference
Mean	-0.001
Abs. Mean	0.025
Min	-0.098
P10	-0.046
P25	-0.018
P50 (Median)	**0.002**
P75	0.024
P90	0.039
Max	0.050

8 SUMMARY OF FINDINGS

IOM's report "Geographic Adjustment in Medicare Payment" proposes revisions for calculating three GPCI components used to adjust physician payments for geographic differences in input cost. Several IOM recommendations for other GPCI components have previously been adopted by CMS (e.g., use of MEI cost share weights, creation of the purchased service index within the PE GPCI) and are not discussed in this report. The changes posed by IOM in the construction of current GPCI components include the following:

- Compute the employee wage components of the PE GPCI using counties as payment areas with wages adjusted for commuting patterns and using data on healthcare workers;
- Use a regression-based approach to measure regional variation in physician wages in the PW GPCI; and
- Identify a source of commercial office rent data to measure regional variation in physicians' cost to rent office space as part of the PE GPCI.

The following discussion summarizes this report's appraisals of each of these sets of recommendations.

8.1 Evaluation of IOM's Employee Wage Recommendations

Through the use of out-commuting shares to weight the wages of physician office employees across MSAs, IOM's first recommendation essentially redefines the GPCI employee wage index as a measure the wage levels associated with the workers who live in a county rather than the workers who are employed in the county. The purpose of a wage index, however, is to measure the earnings of healthcare workers employed in a county, for this represents the costs of labor faced by the providers who hire in the county. The relevant input price physician practices must pay to compete in their pertinent labor market depends not only on the wage levels of individuals living nearby but also on the wage levels paid to attract individuals living outside the local area who work at the practices. As shown in this report, the values of the wage indices associated with healthcare workers living in a county verses the workers employed in a county can be quite different.

Moreover, the IOM smoothing adjustment can produce counterintuitive values for the employee wage index, especially in cases where a large share of workers commute from one MSA to another. Even if all practices in a county pay their workers an identical wage, the IOM method increases these practices' EWI above that wage if workers living in that county commute to MSAs where practices pay higher wages. The reverse is true if workers living in this county commute to MSAs where practices pay lower wages. Further, in the extreme case where all workers in a county out-commute to another MSA, the EWI for physician practices in that county depends entirely on the wage levels paid by practices located in other MSAs.

When IOM's approach is applied in practice, this report concludes that IOM's out-commuting adjustment does reduce the size of cliffs. For counties located within 50 miles of one another in different localities, applying the smoothing algorithm to the employee wage index reduces the differences in GAF values by 0.14 percentage points (i.e., 0.0014) relative to the MSA payment area definition without smoothing. Although the magnitude of this change is small, recall that IOM's recommendation only applies the smoothing algorithm to the employee wage index, and the employee wage index constitutes only 19 percent of the total GAF value. Applying the smoothing methodology marginally reduces the frequency with which nearby counties have GAF differentials exceeding 5 percentage point. Thus, not only does the average difference in GAF values decrease for counties located close to one another, but the share of counties with large cliffs also decreases.

IOM's proposal to measure wages for workers in the healthcare industry rather than across all industries has a number of conceptual advantages and disadvantages but likely would have little effect on GAF values. Calculating the employee wage index using IOM's proposal would permit CMS to identify geographic variation in worker wages that is idiosyncratic to workers in the healthcare industry. If, for instance, regional variation in the wages of nurses employed in physician offices differed from the regional variation in wages for nurses employed by schools, IOM's proposed wage measurement approach would be able to detect these differences. Despite this advantage, the IOM approach has two drawbacks. First, limiting the wage estimates to workers in the healthcare industry reduces the sample size and thus decreases the precision of the wage estimates. This issue could be of particular importance in sparsely populated rural areas. Second, measuring healthcare industry wages across different geographic areas using BLS OES data requires access to confidential BLS OES data, which may be difficult to acquire and would reduce the transparency of the GPCI methodology as providers would not have access to these data. Nevertheless, IOM's own calculations indicate that the correlation between all-industry and healthcare industry wages is over 0.99; thus, the impact on GAF values is likely small in practice.

8.2 Evaluation of IOM's PW GPCI Recommendations

The current construction of the PW GPCI relies on familiar price index theory applied to measure price (and wage) differences across regions and over time. The index forms a market basket of proxy occupations with weights equaling individual proxy occupation's relative share of the national wage bill. The regression framework proposed by IOM, on the other hand, implicitly creates shares in an index that correspond to no market basket. Instead, the coefficients in the index reflect the degree of correlations between the price of one labor commodity and the prices of others across regions. Although difficult to interpret IOM's PW GPCI as characterizing a classic form of a wage index, the IOM approach has a straightforward statistical interpretation as a prediction of the relative regional wages of physicians forecasted using the relative regional wages of comparable occupations. This reduced form specification estimates coefficients that summarize the impacts of a wide range of market factors determining wages, including differences in the relative supplies of occupations across regions and differences in the relative demands for these occupations.

IOM suggests using the sum of the regression coefficients on proxy occupation wages in its regression as a measure of the inclusion factor used in current GPCI policy. One must, however, exercise caution in adopting such an interpretation since this sum, in fact, directly corresponds to a transformed correlation coefficient physicians' relative regional wages and IOM's composite occupation wage index. Consequently, the "IOM inclusion factor" need not be between zero and one as is the case with the inclusion factor under currently policy. The IOM factor can be negative; it can exceed one; and it can even equal zero. Such instances occur in the empirical findings reported here.

An empirical application of a variant of the IOM regression specification using BLS OES data reveals the following findings:

- All regression specifications produce a wide range of coefficient values, including a large number of negative values;
- The regressions produce few coefficients that are statistically significantly different from zero;
- The R-squared measure of fit for the various models varies from 0.19 to 0.65, depending on the diversity and number of MSAs included as observations in the regression; and
- The estimated IOM inclusion factor is near zero or negative.

This report also carries out a number of sensitivity checks, including application of the PW GPCI regressions to ACS data and using an alternative set of proxy occupations. In implementations using ACS data, there is an increase in the share of regression coefficients that are statistically significant, but the model's goodness of fit declines below 0.10. The estimated inclusion factor in the ACS specification becomes positive (0.17). In implementations using alternative proxy occupations, one obtains results largely similar to the findings using the proxy occupations selected under policy.

8.3 Evaluation of IOM's Office Rent Recommendations

IOM's proposal for identifying a source of commercial rent data to compute the office rent index offers a number of attractive features. Although collecting rent data from physicians could improve the accuracy of the office rent index, such an effort would encounter several challenges: (i) collecting a new source of office rent data would be administratively costly, (ii) physician response rates are typically low, (iii) utilizing office rent data collected directly from physicians would introduce a circularity problem, and (iv) developing and collecting a new source of commercial office rent might partially replicate existing data sources currently being studied. This report identifies commercial rent data from CoStar as a potential candidate to replace the residential rent data currently used by GPCI in its calculations. CoStar offers a detailed database that contains national commercial office rent data for over 2.8 million commercial properties covering over 10 billion square feet of space. The database also tracks a wide variety of property types and contains a relatively large number of commercial property listings for rural states. The disadvantages of using CoStar are that it is fairly expensive and—since the data source is proprietary—providers would not be able to fully validate the office rent index calculations. This report recommends that future research should examine the impact of using CoStar commercial rent data on the office rent index. Until these data are studied, however, in the short-term this report recommends the continued use of the large and nationally representative residential rent data available in the ACS.

8.4 Empirical Impacts of IOM Recommendations on GAF Values

To determine whether IOM's recommendations cause a meaningful change in physician GAF values in practice, this report conducts a series of impact analyses of IOM proposals to derive a number of key statistics. Table 8.1 presents these summary statistics. The first column lists the impact analyses carried out in this report. The second column specifies the number of counties or localities used to calculate GAF values. The third and fourth columns describe the median change and absolute mean change. The remaining four columns present the distribution of absolute GAF changes.

The two IOM policy recommendations that induce the largest changes in GAF values consist of modifying the definitions of GPCI payment area and using a regression-based approach to calculate the PW GPCI. In both cases, the average change in GAF values is around 3 percentage points. Since IOM's proposal only applies the out-commuting adjustment to the employee wage index, the changes in county GAF values under the three-tiered payment area are similar in magnitude to what occurs when redefining all GPCI component payment areas to MSAs. Using an alternative set of proxy occupations to calculate PW GPCI values under the current methodology leads to less than a half of a percentage point change in GAF values.

Table 8.1: Distribution of Changes in GAF for Impact Analyses

Proposed IOM Modification	Total Obs.	Median Change	Abs. Mean Change	Distribution of Absolute GAF Changes			
				0.00 to 0.01	0.01 to 0.05	0.05 to 0.10	> 0.10
Three-Tiered Payment Areas	3223 Counties	-0.025	0.028	14.2%	77.8%	7.3%	0.8%
MSA-Based Payment Areas	3223 Counties	-0.027	0.030	13.4%	78.4%	7.5%	0.8%
Regression-Based PW GPCI (FP Specification)	89 Localities	0.007	0.029	24.8%	58.4%	16.8%	0%
Alternative Proxy Occ., Current PW GPCI Methodology	89 Localities	0.000	0.004	96.6%	3.3%	0%	0%

REFERENCES

BOMA (Building Owners and Managers Association). "Building Class Definitions." Accessed March 1, 2012: http://www.boma.org/resources/classifications/Pages/default.aspx.

Boukus, Ellyn R., Alwyn Cassil, and Ann S. O'Malley. "A Snapshot of U.S. Physicians: Key Findings from the 2008 Health Tracking Physician Survey." Center for Studying Health System Change, Data Bulletin No. 35, September 2009: http://www.hschange.com/CONTENT/1078/

Bureau of Labor Statistics (BLS) "Survey Methods and Reliability Statement for the May 2011 Occupational Employment Statistics Survey," 2011, Accessed May 1, 2012: http://www.bls.gov/oes/current/methods_statement.pdf.

Centers for Medicare and Medicaid Services (CMS). "Estimated Sustainable Growth Rate and Conversion Factor for Medicare Payments to Physicians in 2012." Accessed May 31, 2011: http://www.cms.gov/SustainableGRatesConFact/Downloads/sgr2012p.pdf.

Centers for Medicare and Medicaid Services (CMS). "Hospital Inpatient Prospective Payment Systems and 1994 FY Rates." Federal Register 58(100): 30101-30964.

Cummings, S. M., L. A. Savitz, and T. R. Konrad. "Reported response rates to mailed physician questionnaires." Health Services Research. February 2001. 35(6): 1347-1355.

Economic Research Service. "Data Sets: 2003 Rural-Urban Continuum Codes." U.S. Department of Agriculture. Accessed March 2012: http://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx.

"Final Fair Market Rents for the Housting Choice Voucher Program and Moderate Rehabilitation Single Room Occupancy Program Fiscal Year 2012; Notice of Final Fiscal Year (FY) 2012 Fair Market Rents (FMRs)." 76 Federal Regsiter 190 (30 September 2011): http://www.huduser.org/portal/datasets/fmr/fmr2012f/FY2012_FR_Preamble.pdf.

"Final Fair Market Rents for Fiscal Year 2011 for the Housing Choice Voucher Program and Moderate Rehabilitation Single Room Occupancy Program." 75 Federal Register 191 (4 October 2010): http://www.gpo.gov/fdsys/pkg/FR-2010-10-04/pdf/2010-24465.pdf.

Hahn, Jim. "Medicare Physician Payment Updates and the Sustainable Growth Rate (SGR) System." Congressional Research Service. August 2010: http://aging.senate.gov/crs/medicare15.pdf.

Hassmiller, Susan B. and Maureen Cozine. "Addressing the Nurse Shortage to Improve the Quality of Patient Care." Health Affairs 25, no. 1 (2006): 268-274.

IOM (Institute of Medicine). "Geographic Adjustment in Medicare Payment: Phase I: Improving Accuracy, Second Edition." Washington, DC: The National Academies Press. 2011.

MaCurdy, Thomas, Karla Lopez de Nava, Jason Shafrin, Avni Shah, and Thomas DeLeire. "Revising the Medicare Wage Index to Account for Commuting Patterns." Burlingame, CA: Acumen, LLC. April 2011.

MaCurdy, Thomas, Jason Shafrin, Mallory Bounds, and David Pham. "Revisisons to the Sixth Update of the Geographic Practice Cost Index: Final Report." Burlingame, CA: Acumen, LLC. October 2011.

MedPAC (Medicare Payment Advisory Commision). "Physician Services Payment System." October 2010: http://www.medpac.gov/documents/MedPAC_Payment_Basics_10_Physician.pdf.

O'Brien-Strain, Margaret, West Addison, Elizabeth Coombs, Nicole Hinnebusch, Marika Johansson, and Sean McClellan. "Review of Alternative GPCI Payment Locality Structures – Final Report." Burlingame, CA: Acumen, LLC. January 2010.

O'Brien-Strain, Margaret, West Addison, and Nick Theobald. "Final Report on the Sixth Update of the Geographic Practice Cost Index for the Medicare Physician Fee Schedule." Burlingame, CA: Acumen, LLC. November 2010.

Office of the Under Secretary of Defense for Personnel and Readiness. "Military Compensation: BAH Frequently Asked Questions." U.S. Department of Defense. Accessed March 20, 2012: http://militarypay.defense.gov/pay/bah/03_faqs.html.

Reding, Douglas J. "Testimony on Geographic Adjustment Factors in Medicare Payment before The Institute of Medicine." Washington DC: September, 2010. http://iom.edu/~/media/Files/Activity%20Files/HealthServices/GeographicAdjustment/Testimony/Marshfield%20Reding%20Testimony6.pdf .

Reschovsky, James D., and Andrea B. Staiti. 2005. "Physicians incomes in rural and urban America." Washington, DC: Center for Studying Health System Change. Issue Brief No. 92: http://www.hschange.com/CONTENT/725/.

U.S. Census Bureau. "A Compass for Understanding and Using American Community Survey Data." November 2008: http://www.census.gov/acs/www/Downloads/handbooks/ACSMediaHandbook.pdf.

U.S. Census Bureau. "American Community Survey Questionnaire." 2012: http://www.census.gov/acs/www/Downloads/questionnaires/2012/Quest12.pdf.

U.S. Census Bureau. "Design and Methodology: American Community Survey." April 2009: http://www.census.gov/acs/www/Downloads/survey_methodology/acs_design_methodology.pdf.

U.S. Census Bureau. "Geographic Areas Reference Manual." Last Revised January 2012: http://www.census.gov/geo/www/garm.html.

U.S. Census Bureau. "Metropolitan and Micropolitan Statistical Areas." Accessed March 28, 2012: http://www.census.gov/population/metro/.

U.S. Census Burea. "Response Rates – Data." Accessed March, 2012: http://www.census.gov/acs/www/methodology/response_rates_data/.

U.S. Census Bureau. "State & County QuickFacts: Alpine County, California." Accessed March 12, 2012: http://quickfacts.census.gov/qfd/states/06/06003.html.

U.S. Census Bureau. "State & County QuickFacts: San Diego County, California." Accessed March 12, 2012: http://quickfacts.census.gov/qfd/states/06/06073.html.

U.S. Census Bureau. "TIGER Frequently Asked Questions." Accessed March 19, 2012: http://www.census.gov/geo/www/tiger/faq-index.html.

U.S. Department of Housing and Urban Development (HUD). "FMR Documentation: FINAL FY 2012 Fair Market Rent Documentation System." Accessed April 6, 2012: http://www.huduser.org/portal/datasets/fmr/fmrs/docsys.html&data=fmr12.

U.S. Equal Employment Opportunity Commission. "Census 2000 Special EEO File Crosswalk from Census Codes and 2000 SOC Codes to the EEO Occupational Groups and the EEO-1 Job Categories." Accessed April 13, 2012: http://www.eeoc.gov/eeoc/statistics/census/eeo-file-crosswalk.html.

U.S. GAO (Government Accountability Office). "Medicare Physicain Fees: Geographic Adjustment Indices Are Valid in Design, but Data and Methods Need Refinement" Report to Congressional Committees, GAO-05-119, March 2005: http://www.gao.gov/new.items/d05119.pdf.

U.S. GAO (Government Accountability Office). "Medicare: Geographic Areas Used to Adjust Physician Payments for Variation in Practice Costs Should be Revised." Report to the Chairman, Subcommittee on Health, Committee on Ways and Means, House of Representatives. GAO-07-466. June 2007: http://www.gao.gov/new.items/d07466.pdf.

U.S. News and World Report, "Best Hospitals 2011-12: the Honor Roll," July 18, 2011, Accessed March 16, 2012: http://health.usnews.com/health-news/best-hospitals/articles/2011/07/18/best-hospitals-2011-12-the-honor-roll.

Wooldridge, Jeffrey M. "Measurement Error in an Explanatory Variable" *Econometric Analysis of Cross Section and Panel Data.* 2002, Massachusetts Institute of Technology.

Zuckerman, Stephen, and Stephanie Maxwell. "Reconsidering Geographic Adjustments to Medicare Physician Fees." Washington, DC: The Urban Institute. September 2004: http://www.urban.org/publications/411076.html.

APPENDIX A: CURRENT EMPLOYEE WAGE INDEX CALCULATION

Calculating the employee wage using the BLS OES data requires a six-step process. These steps include:

(1) Selecting the occupations for inclusion in the wage index calculation,
(2) Calculating an RVU-weighted national average hourly wage by occupation,
(3) Indexing the wage for each occupation in each MSA to the national median,
(4) Calculating each occupation's share of the national employee wage expenditure,
(5) Calculating MSA-level hourly wage index, and
(6) Calculating locality-level employee wage index values.

The discussion below largely replicates the discussion available in previous reports.[82,83]

A.1 Selecting the occupations for inclusion in the wage index calculation

Step 1 relies on two criteria to identify the occupations to include in the employee wage index. The first criterion excludes physician-related occupations from consideration. This restriction is necessary because the PW GPCI already accounts for regional variation in physician-related occupations. Thus, including physician wages in the PE GPCI would result in double counting.[84] Once the physician-related occupations have been excluded from consideration, the second criterion selects the remaining occupations with non-zero employment within the offices of physicians industry.

A.2 Calculating an RVU-weighted national average hourly wage by occupation

The report first calculates MSA-level median hourly wages (M_{om}) for each occupation using BLS median hourly wage estimates. Using these median wage estimates, one can calculate a national average median wage for each occupation as follows:

(A.1)
$$N_o = \frac{\sum_m RVU_{PE,m} \times MHW_{om}}{\sum_m RVU_{PE,m}}$$

[82] O'Brien-Strain et al. November 2010.
[83] MaCurdy et al. October 2011.
[84] The physician-related occupations are found under the Healthcare Practitioner and Technical Occupations (SOC Code 29-000) major occupation group. A three step approach was used to determine which occupations within this group should be excluded. Acumen first grouped similar occupations, using the second-to-last digit of their SOC code. Each group of occupations was evaluated collectively for inclusion from this point forward. Next, because technical specialties are currently in the employee wage index, any occupation with a '29-2' prefix was included. Finally, our team examined the '29-1' occupational groups for inclusion. Based on the current PE index, registered nurses and physician assistants are considered support staff and were therefore automatically included. Pharmacists were also incorporated in the index. However, the other professions within the '29-1' occupational group—representing different types of physicians and therapists—were excluded. All other occupations, except the ones mentioned above, were considered for inclusion.

where:

N_o = the national hourly wage for occupation group *o*
$MHWo_{om}$ = the median hourly wages for occupation group *o* in MSA *m*
$RVU_{PE,m}$ = the total practice expense RVUs in MSA *m*.

A.3 Indexing the occupation wage in each MSA to the national wage

With the calculation of the national median wages, the MSA median wages for each occupation can be converted to a median wage index, WI_{om}. This index is simply the MSA median hourly wage for the occupation divided by the national wage for that occupation:

(A.2)
$$WI_{om} = \frac{MHW_{om}}{N_o}$$

where:

WI_{om} = the wage index for occupation *o* in MSA *m*
MHW_{om} = the average hourly wages for an occupation group *o* in MSA *m*
N_o = the national hourly wage for occupation group *o.*

A.4 Calculating occupations' share of the national employee wage expenditure

To create a single composite index across multiple occupations, the fourth step weights each occupation relative wage by its wage bill within the offices of physicians industry. These weights can be calculated as follows:

(A.3)
$$B_o = \frac{N_o \times CS_o}{\sum_o N_o \times CS_o}$$

where:

B_o = the wage bill share associated with occupation *o*
N_o = the national hourly wage for occupation *o*
CS_o = the cost share for occupation *o.*

A.5 Calculating MSA-level hourly wage index

The final step uses the occupational shares from step 4 to create wage indices for each MSA that weight the individual occupational indices by the occupational shares. This is calculated as the sum of the product of the MSA-level indices for each occupation times the wage bill share for each occupation, represented by the following equation:

(A.4)
$$EWI_m = \sum_o (WI_{om} \times B_o)$$

where:

EWI_m = the employee wage index for MSA *m*
WI_{om} = the wage index for occupation *o* in MSA *m*
B_o = the share of the wage bill associated with occupation *o.*

The resulting MSA-level index provides values for all MSAs and territories for which BLS wage data are available. This excludes the Virgin Islands, Guam, and American Samoa. Currently, Guam and American Samoa are treated as missing and are ultimately assigned the Hawaii locality value. Given the absence of data for the Virgin Islands, the value for each area within the Virgin Islands locality is set equal to 1.

A.6 Calculating locality-level employee wage index

The final step creates the employee wage index values at the locality level. To move from MSA to locality levels, one simply calculates a weighted average of all MSA-level EWI values in that locality where the weights are the PE RVUs for each MSA in that locality. Mathematically:

$$EWI_l = \frac{\sum_{m \in M_l} RVU_{PE,m} \times EWI_m}{\sum_{m \in M_l} RVU_{PE,m}} \tag{A.5}$$

where:

EWI_l = the employee wage index in locality l,
EWI_m = the employee wage index in MSA m
$RVU_{PE,m}$ = the total practice expense RVUs in MSA m.
$m \in M_l$ = all MSAs in locality l

APPENDIX B: IMPACT OF IOM'S MSA-BASED PAYMENT AREAS

In Recommendation 2-1, IOM proposes discontinuing the use of Medicare localities to define PE GPCI payment areas and replacing these payment areas with ones defined using MSA boundaries. Section 4 of this report previously evaluated the pros and cons of defining labor markets using MSAs rather than localities. This section, however, presents a brief analysis of alternatively-based payment areas in three parts. Section B.1 reviews two additional candidate payment area definitions in conjunction with MSAs and the current Medicare localities: county and statewide tiers. Section B.2 analyzes the effects of these four different payment area definitions on the distribution of the GAF values, and Section B.3 concludes by investigating the impact of the different payment area definitions on the presence of GAF cliffs.

B.1 Payment Areas Definitions

Although there are a number of alternative ways in which the current locality structure of 89 GPCI payment areas could be refined into a geographic partition that better reflects economically integrated geographic areas, this report considers the following four candidate payment area definitions:[85]

- County
- MSA (proposed by IOM)
- Locality (status quo)
- Statewide tiers

All four candidate payment areas are defined as combinations of counties. As its name suggests, the county-based payment area system uses the politically-defined county as the unit of analysis. While the MSAs (proposed by IOM) and Medicare localities (status quo) are both aggregations of counties, MSAs are agglomerations of economically-integrated counties, whereas Medicare localities are not. The statewide tier payment area, presented in the July 2007 proposed rule as "Option 3," combines counties into tiers within each state based on each county's GAF value. Since the statewide tiers are constructed according to county GAFs rather than according to a county's proximity to and economic relation with metropolitan areas, the counties grouped into tiers need not be contiguous. The statewide tiers option defines payment areas based on the following five steps:

(1) Rank counties in descending order by their GAFs.
(2) Assign the county with the highest GAF to the first payment area or "cost tier" and define the "standard" for that first cost tier based on the highest county GAF.

[85] For a more detailed discussion, see O'Brien-Strain, Margaret, West Addison, Elizabeth Coombs, Nicole Hinnebusch, Marika Johansson, and Sean McClellan, "Review of Alternative GPCI Payment Locality Structures", Acumen LLC, 2008.

(3) Compare the GAF for the county with second highest GAF to the standard for the first tier. If the difference is less than five percent, assign the county with the second highest GAF to the first tier.
(4) If the difference is greater than or equal to five percent, the county is instead placed in a new (second) cost tier, and its GAF becomes the standard for that tier.
(5) Iterate through all counties in the state, starting a new tier whenever a difference in GAFs is five percent or greater.

Consider a simple example to illustrate these steps. Start with a given state, ranking its *N* counties from highest (called County *1*) to lowest (called County *N*) by their GAF values. The standard for the first tier in that state is GAF_1, which is the GAF of the state's highest-cost county, (i.e., County *1*). County *2*, which has a GAF value denoted GAF_2, is assigned to a tier on the following basis. If $GAF_1/GAF_2 < 1.05$, then County *2* is assigned to Tier 1. Suppose that is the case. Then the next step is to consider County *3*, which has a GAF value of GAF_3. If $GAF_1/GAF_3 < 1.05$, then County *3* is also assigned to Tier 1. Supposing that is the case, consider County *4*, with GAF value GAF_4. If $GAF_1/GAF_4 < 1.05$, then County *4* is also assigned to Tier 1. But suppose instead that $GAF_1/GAF_4 \geq 1.05$. Then County *4* is assigned to Tier 2 and becomes the standard for that new tier (analogous to County *1* for Tier 1). The process then continues, so that County *5* is assigned to either Tier 2 (if GAF_2/GAF_5 is less than 1.05) or Tier 3 (if GAF_2/GAF_5 is greater than or equal to 1.05), and so on. This assignment process continues until all *N* counties in the state are compared against the standards for the preceding tier. The number of tiers in a state will depend on the distribution of GAFs in the state.

This report maps county-level data to statewide tiers using the iterative methodology just described. All GPCI values computed in this section were calculated using 2009 RVUs and the methodology specified in the CY2012 final rule.

B.2 Measuring Variability Across Four Candidate Payment Areas

The first analysis examines the distribution of GAF values across the four payment area definitions. Table B.1 provides summary statistics for the four alternate payment area definitions. To facilitate a comparison across payment area definitions, all of the descriptive statistics are reported at the county level. For example, if there are three counties in a Medicare locality, each county is considered a separate observation even though they all receive the same GAF value. Note that the average RVU-weighted averages (reported in the first row of Table B.1) are not equal to one because these GAF values are displayed prior to final adjustments for budget neutrality.[86]

Among the four different payment area definitions, the county-based definition exhibits the most variability in GAF values, and the Medicare locality payment area definition displays

[86] These adjustments include adding localities without data available (e.g., Guam) and adjusting locality RVU levels to incorporate RVUs that cannot be assigned to specific counties.

the least variability. Whereas the range of GAF values for the county-based payment areas is 0.442, the corresponding value for the Medicare locality is 0.414. The standard deviation calculated for the county-based payment areas is about 10 percent larger than the standard deviation for the Medicare localities. The standard deviations for the MSA and statewide tier definitions are comparable to that of the county-based definition but exhibit a narrower range of GAF values.

The locality-based methodology has the smallest standard deviation and range because these payment areas are large and, by definition, do not permit within-locality variation in county GAF values. This lack of variability is desirable only to the extent that it reflects the true regional variation in input prices. As discussed above, however, the locality-based definition likely does not represent a homogenous market for the physician practice inputs, since localities are not based on any measure of economic activity. Thus, the lack of intra-locality GAF value differences likely disguises input price variability for physician practices located in different parts of each locality.

Table B.1: Summary of GAF Values by Alternate Payment Areas

Statistic		Medicare Locality	County	MSA	Statewide Tier
Average, RVU Weighted		0.999	0.999	0.999	0.999
Average, Unweighted		0.941	0.920	0.923	0.924
Std. Dev.		0.050	0.055	0.055	0.055
Range		0.414	0.442	0.423	0.423
Minimum		0.771	0.742	0.759	0.742
Percentiles	**5**	0.896	0.866	0.866	0.867
	10	0.903	0.874	0.874	0.874
	25	0.910	0.885	0.886	0.888
	50	0.937	0.909	0.909	0.915
	75	0.962	0.944	0.946	0.944
	90	0.999	0.988	0.991	0.991
	95	1.032	1.020	1.023	1.023
Maximum		1.184	1.184	1.182	1.165

B.3 Measuring Variability Across Four Candidate Payment Areas

To identify the presence of cliffs across the candidate payment area definitions, this report carries out two separate analyses. The first analysis estimates the average difference in GAF values between county pairs (the two counties making up a pair are each located in a different locality). In general, one would expect counties that are located close to one another to have similar GAF values. However, even if the average difference in GAF values is small, this finding does not rule out the presence of large differences in GAF values for certain counties.

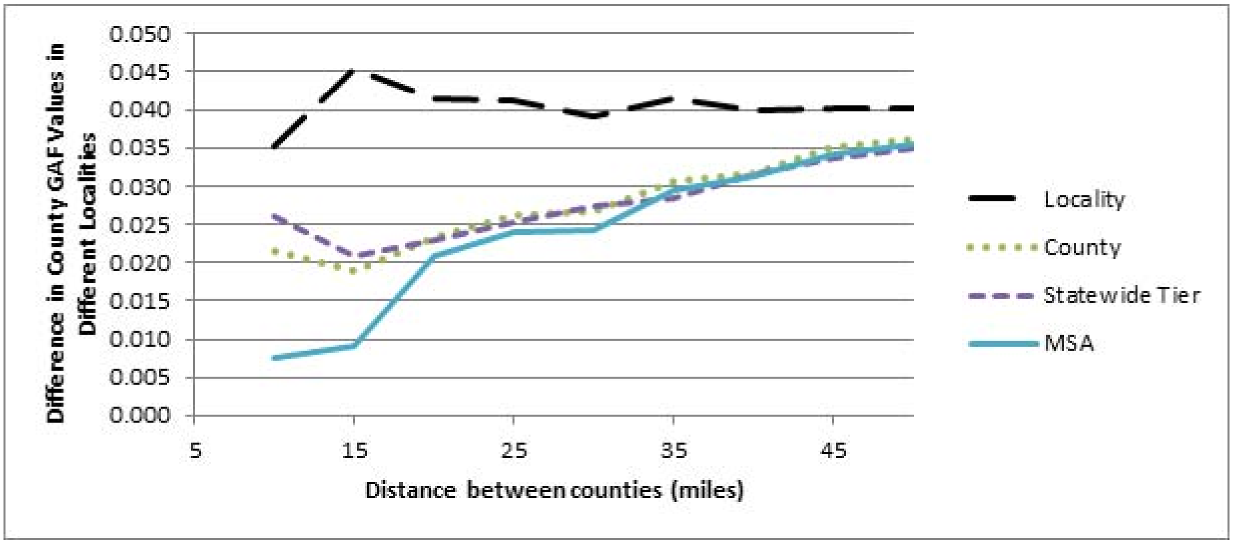
Thus, the second analysis examines the share of nearby counties with "large" GAF differentials. The analysis defines a large difference as 5 percentage point difference in GAF values.

This report relies on a number of key steps to conduct these two cliffs analyses. First, this report calculates the GAF for each county. Second, this report calculates the absolute GAF difference between each county and all other counties. Third, this report relies on 2000 Census data to identify the latitude and longitude of the center of each county and calculate the distance between the county pairs.[87] Finally, because all counties in the same locality receive the same GAF value, this report restricts the sample to counties located in different localities. For each of the four candidate payment area definitions, this report analyzes the differences in GAF values by distance between county pairs.

Whereas the locality-based payment area definitions create the largest average GAF differences between physician practices located in nearby counties but in different localities, the first cliffs analysis reveals that the MSA-based payment area definition produces the smallest differences in GAF values. Figure B.1 graphically depicts the results of the first cliffs analysis. Because physicians in the same locality receive the same GAF values under the current system, the data underlying Figure B.1 only include county pairs where the two counties are in different localities. In this sample, there are no counties in different localities whose centers are within 5 miles of one another. From the figure, however, the MSA-based payment area definition reduces the average GAF differences in counties within 20 miles of one another by more than half. For instance, counties between 5-10 miles of one another (i.e., 10 on the x-axis) and counties between 10-15 miles of one another, have an average absolute difference in GAF of less than 0.010 using the MSA payment definition, but more than 0.035 using the locality-based payment definition. For counties located between 20 and 50 miles of one another, the MSA, county and statewide tier payment area definitions perform similarly. The locality payment area definition, however, performs worst in terms of creating cliffs between counties located in different localities.

[87] Census calculates the latitude and longitude of each county as the approximate geographic center of the polygon making up the legal entity. For more information, see: U.S. Census Bureau. "TIGER Frequently Asked Questions." http://www.census.gov/cgi-bin/geo/tigerfaq?Q18.

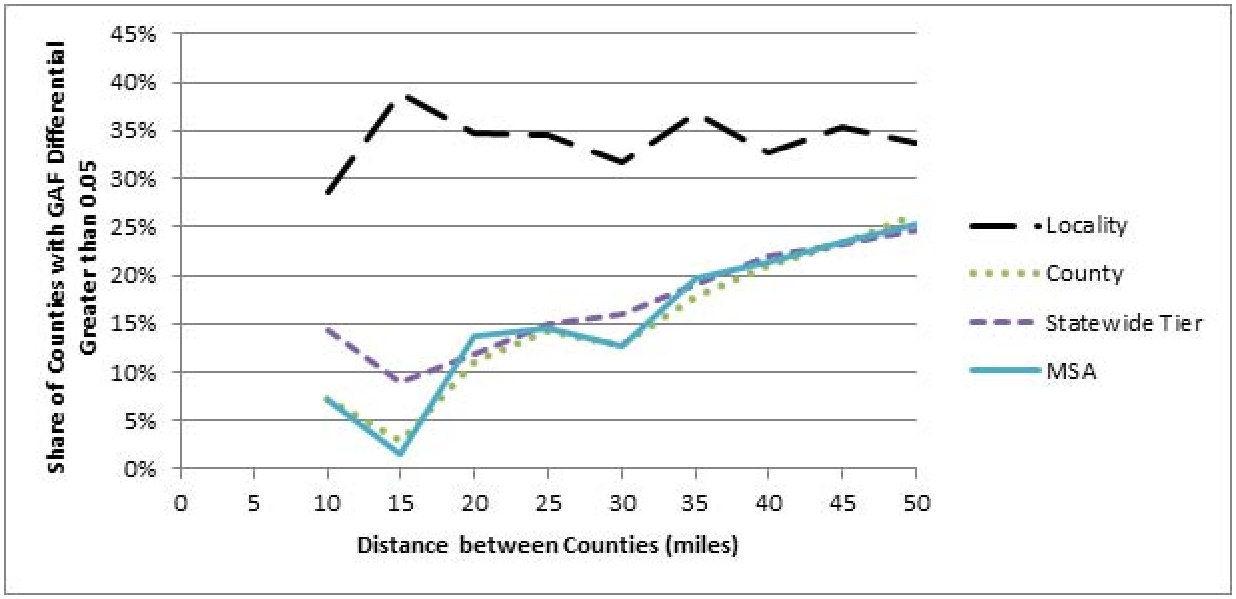
Figure B.1: Difference in County GAF Values in Different Localities by Distance



The second cliffs analysis reveals that, among the four candidate payment areas, the MSA-based and county-based payment areas are least likely to have GAF differentials of more than 5 percentage points for nearby counties. Figure B.2 displays the graph of the share of nearby counties with a GAF differential of more than 0.05 against the distance between the counties. The MSA-based and county-based payment area definitions create a cliff of this size in less than 10 percent of cases for counties within 15 miles of one another. Further, MSA, county and statewide tier payment definitions create cliffs for less than 15 percent of counties that are within 25 miles of one another. On the other hand, cliffs are much more frequent using the locality definition. For counties within 10 miles of one another, 29 percent of county pairs have a GAF differential of more than 5 percentage points when locality-based payment areas are in place. For counties between 10 and 30 miles of one another, generally one-third of county pairs have a GAF differential greater than 0.05.

Redefining cliffs as a GAF differential of at least 10 percentage points produces similar results (not shown). Whereas 7 percent of counties within 30 miles of one another have a GAF differential greater than 0.10, the corresponding figures for the county, MSA and statewide tier payment areas are 2 percent, 3 percent, and 2 percent, respectively.

Figure B.2: Share of Counties with GAF Differential Greater Than 0.05 by Distance



Using distance to determine whether physicians in different counties face similar labor markets provides a useful measure of the similarity of input price markets. Counties that are close together are more likely to face similar input prices, because if the input prices differed greatly, physicians would have an incentive to purchase their inputs from a nearby county or to relocate their office. Thus, physician practices that are in close proximity generally face similar input price markets. However, if a barrier (e.g., a mountain range) exists between two physician practices located in close proximity to one another, these practices could face different markets for practice inputs. In this case, the appearance of a cliff in the GAF values of adjacent counties would represent a real difference in input prices. Although these barriers do appear in certain local markets, this report assumes that these barriers appear relatively infrequently and, thus, distance between counties provides a reasonable proxy for labor market similarity across all counties.

APPENDIX C: UNWEIGHTED PW GPCI REGRESSION

In addition to the PW GPCI regression-based approach presented in Section 5.3, this report also conducts a separate analysis using an alternative "unweighted" regression framework. In the baseline specification in the body of the paper, IOM's PW GPCI regression methodology uses a weighted ordinary least squares specification where the weights are the number of PW RVUs in each MSA. The alternative regression presented in this appendix, on the other hand, gives all MSA-level observations equal weight.

The following tables provide an overview comparing the results from this unweighted BLS regression specification against the PW RVU-weighted regression results presented in Section 5.3. Table C.1 implements both regression specifications using the existing proxy occupations; Table C.2, on the other hand, implements both regression specifications using the alternative proxy occupations described in Section 5.4. These tables show that the goodness-of-fit of the unweighted regression is always lower than the weighted regression. Further, the IOM inclusion factor estimated from the unweighted regression is negative in three of the four unweighted specifications below, but is around 0.10 for the specialty mix regression. The unweighted specification also has fewer statistically significant coefficients using the original proxy occupations, but has a similar (or higher) number of statistically significant coefficients when the alternative set of proxy occupations are used in the regression model.

Table C.1: Weighted vs. Unweighted PW GPCI Regressions (Original Occupations)

Specification	R-Squared	Inclusion Factor	Statistically Significant Coefficients				Total Coefficients (excl. intercept)
			1%	5%	10%	Total	
Specialty Mix							
Weighted	0.652	-0.001	0	2	4	6	19
Unweighted	0.518	0.099	0	2	1	3	19
Family/General Practitioner							
Weighted	0.194	-0.168	1	1	0	2	19
Unweighted	0.066	-0.350	0	0	0	0	19

Table C.2: Weighted vs. Unweighted PW GPCI Regressions (Alternate Occupations)

Specification	R-Squared	Inclusion Factor	Statistically Significant Coefficients				Total Coefficients (excl. Intercept)
			1%	5%	10%	Total	
Specialty Mix							
Weighted	0.351	-0.077	0	0	1	1	9
Unweighted	0.215	-0.050	0	1	1	2	9
Family/General Practitioner							
Weighted	0.107	-0.145	0	1	1	2	9
Unweighted	0.063	-0.057	0	1	1	2	9

APPENDIX D: ALTERNATIVE SPECIFICATION FOR THE PROXY OCCUPATIONS

This report uses an "alternative" set of occupations in an effort to implement IOM's recommendation to "empirically re-evaluate the accuracy of the 7 proxies it currently employs using the most current BLS OES data."[88] These alternative occupations were selected based on three criteria:

(1) Non-physician occupations where more than 80 percent of workers have a bachelor's degree;
(2) Excluding occupations that constitute more than 5 percent of physician offices' non-physician labor expenses; and
(3) Excluding occupations without wage data in a sufficient number of payment areas.

When applying working with these occupations in any data set, this report adds a restriction that the occupations have non-missing wage data for at least 50% of nationwide RVUs. The occupations that met these four requirements are detailed in the following table. All 31 occupations below are included in the PW GPCI calculation that relies on the current CMS methodology.

Table D.1: Summary Statistics for Alternative PW GPCI Proxy Occupations

SOC Code	Occupation Description	Share with BA	Hourly Median Wage	Hourly Mean Wage	Total Employment	Share of Wage Bill	Share of RVUs with Data
23-1011	Lawyers	98.0%	$53.17	$59.98	553,690	19.8%	98.6%
15-1031	Computer software engineers, applications	81.3%	$41.07	$42.26	494,160	12.5%	93.4%
15-1032	Computer software engineers, systems software	81.3%	$44.44	$45.44	381,830	10.3%	88.4%
29-1051	Pharmacists	94.5%	$51.16	$50.13	266,410	8.0%	99.9%
11-9041	Engineering managers	82.6%	$55.42	$57.97	182,300	6.3%	94.7%
17-2051	Civil engineers	82.2%	$35.87	$37.77	261,360	5.9%	97.9%
13-2051	Financial analysts	84.1%	$35.17	$40.76	236,720	5.8%	86.1%
29-1123	Physical therapists	88.6%	$35.00	$35.77	167,300	3.6%	98.9%
17-1011	Architects, except landscape and naval	87.6%	$33.81	$36.90	110,990	2.4%	83.0%
25-4021	Librarians	80.2%	$25.26	$26.30	151,170	2.4%	98.8%
19-1042	Medical scientists, except epidemiologists	97.9%	$34.90	$39.36	99,750	2.3%	57.7%
29-1127	Speech-language pathologists	97.4%	$30.25	$31.80	107,340	2.0%	95.9%

[88] IOM 2011, p. S-12.

SOC Code	Occupation Description	Share with BA	Hourly Median Wage	Hourly Mean Wage	Total Employment	Share of Wage Bill	Share of RVUs with Data
19-3031	Clinical, counseling, and school psychologists	98.8%	$30.84	$33.74	97,880	2.0%	91.0%
29-1122	Occupational therapists	90.0%	$32.10	$32.65	94,800	1.8%	95.4%
19-2031	Chemists	90.6%	$31.84	$34.17	83,080	1.7%	84.2%
25-1194	Vocational education teachers, postsecondary	91.1%	$22.76	$24.46	112,940	1.6%	84.3%
11-9121	Natural sciences managers	90.8%	$54.23	$59.20	43,060	1.5%	66.9%
19-2041	Environmental scientists and specialists, including health	92.2%	$28.72	$31.39	80,120	1.5%	87.6%
29-1131	Veterinarians	98.7%	$38.01	$43.00	53,110	1.4%	89.1%
17-2081	Environmental engineers	87.3%	$35.59	$37.49	52,590	1.2%	80.3%
19-2042	Geoscientists, except hydrologists and geographers	92.2%	$38.06	$42.93	31,260	0.8%	62.2%
17-2041	Chemical engineers	87.1%	$40.71	$42.67	30,970	0.8%	63.7%
29-1199	Health diagnosing and treating practitioners, all other	85.4%	$31.67	$37.76	34,890	0.8%	61.4%
19-3051	Urban and regional planners	92.1%	$28.75	$30.00	37,120	0.7%	76.5%
19-3099	Social scientists and related workers, all other	86.0%	$33.04	$34.49	28,680	0.6%	57.1%
19-1029	Biological scientists, all other	92.8%	$31.29	$32.71	28,290	0.6%	61.4%
15-2011	Actuaries	95.4%	$40.77	$46.14	18,220	0.5%	52.8%
15-2041	Statisticians	87.5%	$34.91	$35.96	20,680	0.4%	54.8%
17-1012	Landscape architects	87.6%	$28.35	$30.77	21,130	0.4%	58.6%
19-1031	Conservation scientists	83.0%	$28.23	$28.93	15,830	0.3%	53.0%
29-1121	Audiologists	92.8%	$29.82	$31.49	12,480	0.2%	55.5%

This report also uses these proxy occupations to calculate the PW GPCI values under IOM's recommended regression-based methodology. Whereas all 31 occupations are used to calculate the PW GPCI under the current CMS approach, when applied within IOM's regression-based methodology not all these occupations are used. To be included as an independent variable in the IOM PW GPCI regression, this report requires the proxy occupations to have populated wage data for all MSAs where the dependent variable (i.e., the direct measure of physician wages) has observable wage data. After imposing this restriction, only nine of the alternative proxy occupations remain for inclusion in the regression.

Table D.2 contain results from implementing IOM's regression-based approach using the alternative proxy occupations. The top panel of the table contains the regression coefficients and their respective level of statistical significance. The bottom panel contains the number of MSAs included in the regression, the R-squared, and IOM's estimated "inclusion factor."

Table D.2: Regression Results for PW GPCI Using Alternative Occupations

Variable	Multi-Specialty	Family Practice
Intercept	1.001 ***	1.145 ***
Pharmacists	0.033	0.104
Lawyers	-0.308 *	-0.081
Librarians	0.108	-0.169
Physical therapists	-0.188	0.091
Civil engineers	0.269	-0.134
Speech-language pathologists	0.134	0.081
Engineering managers	-0.263	-0.179 *
Occupational therapists	-0.072	-0.071
Computer software engineers, applications	0.211	0.213 **

Stars indicate level of significance: * = reject zero at 10%; ** = reject zero at 5%; and *** = reject zero at 1%.

Statistic	Multi-Specialty	Family Practice
Number of MSA	36	237
R-Squared	0.351	0.107
Estimated "inclusion factor"	-0.078	-0.145