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Monitoring Regional Access With Administrative Data

This brief presents two methods that state Medicaid agencies can use to assess regional differences in access. Both methods derive from traditional statistical methods sometimes used in clinical research to compare test and control populations, but useful also in comparing populations that are different in personal characteristics, that might affect use of services independent of regional differences in access. The brief discusses the advantages and challenges of these methods and provides examples of how they might be applied in the context of monitoring access for Medicaid enrollees.

About this series: The Medicaid Access Technical Assistance brief series is intended to serve as a resource to state Medicaid agencies by providing options and strategies for completing their access monitoring review plans (AMRPs). In November 2015, CMS released a final rule directing states to use a data-driven approach to examine access for beneficiaries in fee-for-service (FFS) Medicaid (Methods for Assuring Access to Covered Medicaid Services, CMS-2328-FC). The final rule requires that, starting in October 2016 and every three years thereafter, states submit an AMRP to report data on access to care and compare their Medicaid rates with rates paid by Medicare and private payers (commercial insurers) for services that are covered on a FFS basis.

A. Introduction

Many public comments offered before release of the final rule for Medicaid Access Monitoring Review Plans (AMRPs) indicated the importance of understanding levels and changes in access in different geographic regions within states in order to target resources effectively.[1] The final rule does not define state geographic areas or the specific geographic considerations that states must heed in their access reviews. Instead, each state may determine whether and how to report the geographic considerations it deems appropriate. In their 2016 AMRPs, 37 states presented one or more access measures at a regional level for at least one service type.

This brief offers information about methods and data that might be used to identify and interpret differences in access between Medicaid fee-for-service (FFS) populations in two or more regions of the state. The target audiences for this information include Medicaid agency staff who conduct analysis for the AMRPs and senior staff who supervise and act on these findings. Implementing the methods described in this brief requires that the analyst have sufficient statistical sophistication to use software such as SAS, STATA, or R for analysis of large data sets, and to interpret the results appropriately. If using smaller data sets, the analyst might use Excel for simple regression and other estimates. States that wish to partner with a university or consultant to develop regional comparisons might use the information in this brief for background on what such an analysis might include.

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The discussion assumes that the state will principally use its own administrative data—including, in particular, enrollment and claims-level data—to identify regional differences in access. States might define regions as counties or multicounty areas, or develop regional definitions from zip-code information on enrollees' location of residence. While some methods may entail supplementing administrative data with population survey data, we assume that survey data would not be the primary source of information, so that the analysis would not need to address problems that might arise from small regional population samples.

B. Analytic issues and methods for comparing by region

Regional differences in population demographics or other factors that might affect the demand for health care services can complicate comparisons of access. Measured without regard to demographic or other differences, apparently similar use of services can mask important differences in access.

When regional differences in the demand for services might be explained by factors other than access, analysts sometimes stratify the populations to produce more comparable population subgroups for direct comparison. However, even accounting for just a few characteristics of the population may require stratifying enrollees in each region into multiple subgroups. This approach can easily produce an unwieldy number of strata per region.[2]

This brief describes two alternative methods that states might use to compare unlike enrollee populations across regions. These methods include (1) multivariable regression modeling to identify systematic differences in service use between or among regions, and (2) population-weighted analysis to balance differences across regional populations.

1. Regression-adjusted estimates

States that wish to identify whether there is a significant, systematic difference between or among regions might estimate a simple regression model to explain differences in a selected measure of access. This technique produces "regression-adjusted" estimates of regional differences controlling for potential confounders such as the demographic composition of the population or other characteristics that might affect an enrollee's likelihood of seeking care.

To adjust estimates of regional differences controlling for such confounders, the analyst would estimate a multivariable regression model such as the following, to predict access to medical services (M) by each enrollee (i):

$$M_i = \alpha + bX_i + cR_i + e_i$$

In this formulation, M_i might be defined as the number of services of a particular service type (as defined in the AMRP) that each enrollee uses.[3] The enrollee's personal characteristics, X_i, would be a series of variables that might affect the likelihood of seeking care—potentially including each enrollee's sex, age, race, eligibility category, and presence of relevant comorbidities indicating enrollees' burden of illness.[4] Confounders might be measured as continuous variables (such as age in years) or indicator variables (for example, 1 = male). In general, X_i would include characteristics that would be expected to predict the individual's use of health care services if not constrained by access to care.

R_i would be an indicator variable for the individual's location of residence. It might compare two locations (for example, urban versus rural enrollees) or several locations (for example, metro area 1, metro area 2, eastern rural, and western rural). When using a categorical variable to designate region, the analyst must choose a reference region—that is, it is the region to which all others are compared.

Typically, the region with the largest number of Medicaid enrollees would be chosen as the reference region. For each resident of the reference region, the value of $R_i$would equal zero; for residents of the comparison region, R_i would equal 1. When comparing access across three or more regions, R_i would be a series of categorical variables, one variable for each region excluding the reference region. The value of each region variable would equal to 1 if the enrollee lives in that region and if not it would equal zero.

Finally, in this model, e_i represents the error term, which indicates how well the model fits the data. Every regression software package will calculate the error automatically and provide statistics (such as a model t-test and r^2 statistic) that indicate how well the model fits the data.[5]

Having controlled for population characteristics that might confound interpretation of observed differences in the measure of access, the coefficient estimated for each region would be interpreted as the systematic difference in per-person service use associated with residence in that region relative to the reference region, independent of differences in the measured characteristics of the population. To illustrate differences in the measure of access, the analyst would "predict" average (or mean) utilization using the estimated coefficients, as shown in Figure 1.

Figure 1: Example of regression-adjusted estimates

We estimated the equation $M_i = \alpha + bX_i + cR_i + e_i$ using ordinary least squares (OLS) regression, where M_i is defined as the number of pediatric primary care services used, X_i is the age of the child under age 12, and R_i is defined as rural residence (versus urban, the control region).

For this analysis, we used the Excel LINEST function on a small data set. We estimated parameters for a, b, and c, as shown below; all were statistically significant, based on the calculated t statistic. The results indicate that controlling for age, children residing in rural areas use, on average, about one less primary care service per child (c = 0.92) than children in urban areas use.

a	b	c
-0.21389	2.73611	-0.92037

Estimated OLS parameters

Using the estimated parameters, we predicted average use in each region and compared average predicted use with average actual use, as shown below:

Region	Actual	Predicted
Rural	0.9	10.7
Urban	1.9	13.5

Estimated actual and predicted use per child

Recall that the predicted values have no real meaning; only the relative values are meaningful. Therefore, we would report the following table:

Actual ratio	Regression-adjusted ratio
47.6%	79.6%

Estimated actual and regression-adjusted ratios of use per rural child to use per urban child

The comparison shows that actual average use in rural areas is less than half the average use in urban areas (47.6%). However, when regression-adjusted for enrollee age, average use among rural children (while still lower than among urban children) is substantially more equal (79.6%).

The actual levels of primary care use among both rural and urban children could be clinically meaningful. Nevertheless, improving access among rural children to achieve the same level of use as among urban children might be more attainable than it appears based only on unadjusted estimates.

If the region coefficient (b = 2.74) were insignificant, we would report no difference in access by region after controlling for children's ages. However, because age is significant, we might report differences in access related to age groups that vary by region. We would state that the observed regional differences in the measure of access are known to relate to differences in the average ages of children in each region versus other, unmeasured factors that might vary by region.

Regression analysis might also be used to assess the statistical significance of a change in access across regions over time—that is, to identify whether access in one or more regions relative to the reference region has improved or deteriorated. This analysis would require use of somewhat more complex methods, as well as data that include comparable measures of access in each region over two or more time periods.[6]

Despite the strengths of regression adjustment for measuring regional differences in access, several caveats are in order. First, a regression model would almost certainly not control for every factor that might affect demand for services. If omitted variables are uncorrelated with regions, the omission will not bias the estimated region coefficient. Conversely, if the omitted variables are correlated with regions, the omission will bias the estimated region coefficient and affect interpretation of the result. Consequently, the analyst should carefully consider what unobserved variables might affect whether a beneficiary seeks care and whether those variables are correlated with region. Such factors might include language or economic barriers (for example, among families of day laborers) and point to potential solutions that might not otherwise be considered. States might consider using survey data—such as the American Community Survey (ACS) or state-based surveys that are representative of regional populations—to better understand what relevant variables vary by region and, because those variables are not captured in administrative data, affect interpretation of estimates derived only from administrative data.

Second, if the observed characteristics of the comparison groups are very different, the regression-adjusted estimates can vary depending on the particular form of the model.[7] In this case, it is important that the analyst test alternative models to assess the stability of the estimates.

Finally, although the estimated coefficient might indicate statistically significant regional differences in access, the measured differences might not be clinically meaningful. For some services (such as preventive services), clinical significance might be easier to establish than for others (such as surgical services), where clinical need may be more difficult to predict.[8]

2. Comparing population-weighted differences
This method assigns a population weight to each enrollee (or each category of enrollees) in the region in order to make an "apples-to-apples" comparison between regions. An analyst using this method would assign a weight to the population of each region to account for one or more characteristics that would confound simple comparison. After weighting, the distribution of both populations with respect to the selected characteristics will resemble, in the aggregate, the same benchmark population.[9]

For example, the total statewide population might be selected as the benchmark. In this case, each person (or category of persons) in each region would be weighted to reflect the relative frequency in the state of a person with the selected key characteristics. Alternatively, each regional population can be reweighted so that the each individual (or stratum of individuals, as in the example below) is equally likely to occur within and across regions, erasing distributional differences.

A simple, two-region example is shown Figure 2, considering only one confounding characteristic: population age. In the example, both Region 1 and Region 2 are weighted so that the distribution of enrollees by age category is equal within each region, as well as equal across regions. In actual practice, it would be desirable to use person-level (versus categorical) data, and also to re-weight for a greater number of factors that might confound simple comparison of unweighted measures of access. Such factors might include age, gender, and ethnicity, as well as eligibility category and one or more burden of illness measures. To account simultaneously for such factors when using person-level data, any of several methods can be used—including population "raking"[10] or use of propensity scores to calculate the population weight. These two methods are described briefly below.

Population raking. Also called "population balancing," raking allows the analyst to benchmark the population of each region to a standard population such as the total population across regions. Once benchmarked to a standard population, remaining differences in access among regions would be attributable to factors that do not include those that were considered in the raking. Raking procedures are available in statistical software such as SAS.[11]

Propensity scoring. Propensity scoring can be used to calculate population weights that account for multiple characteristics of the population that are not equally distributed among regions. To calculate propensity scores, the analyst would estimate a person-level model to predict an enrollee's location in one region (versus a reference region), controlling for an array of measured personal characteristics.[12] Each person's propensity score is their predicted probability of residing in that region, as generated from the model. The person weight is then calculated as the inverse of the estimated propensity score (1/p), and the population-adjusted regional measure of access is calculated as the simple average of the weighted measure, in the same way as shown in Figure 2.[13]

Analysts and policymakers should be aware that population-weighted measures, regardless of the method used to produce them, do not produce reportable numbers because they are based on a hypothetical population. Instead, they are useful only to make valid comparisons between populations. After population-weighting, the estimates represent populations that are made to look like each other in one or more key characteristics that, independent of region, might affect access to services.

The remaining regional difference is a measure of unequal access, if any, attributable to factors other than differences in the populations. In the example shown in Figure 2, the regional difference is the difference in access that would be expected if someone selected from Region A were placed in Region B. By doing this analysis, the state will be able to discern whether an apparent difference in a measure of access is related primarily to regional differences in the selected population characteristics or to other regional factors that might be investigated further.

C. Discussion

Differences in regional populations that would affect the likelihood of seeking services can confound comparisons among regions. However, state administrative data—including especially fee-for-service enrollment and claims data—offer a rich source of information that the states can use to conduct analyses that control for regional population differences.

The choice of one method over another is driven by the data available and the statistical expertise within or available to the team conducting these analyses. In addition, some population survey data (such as the ACS or, in some states, a state-sponsored population survey) are valid at a regional level. These data can be used to validate the extent and direction of regional population differences (such as race/ethnicity, educational attainment, or occupation) that are not captured in administrative data and, therefore, may not be controlled for in regional analyses that use only administrative data.

By using these methods and thoughtfully interpreting and presenting the results, state staff can provide valuable information to experts and policymakers about why regional differences in access among Medicaid FFS enrollees exist, and begin to assess the sources of regional differences that should be investigated further.

Figure 2: Example of population-weighted estimates

We want to adjust a measure of specialist visits per enrollee to account for differences that are potentially attributable to differences in population age. The number of enrollees in each age group and region are shown in the table below.

To adjust the regional populations for differences in their age distributions, we first estimate the probability that beneficiaries within each region would be in each age group. In Region 1, for example, the probability that a beneficiary would be age 0–17 is 1,200/6,000 = 0.20. We calculate the population weight for each age group in each region as the inverse of the probability (1/probability) of being in a specific age group.

Population-weighting to compare specialist visit rates

	Number of enrollees	Within-region probability of being in age group	Estimated population weight	Total visits	Visits per enrollee	
					Observed (unweighted)	Population-weighted
Region 1	6,000	1.00	—	3,700	0.62	0.64
Age 0–17	1,200	0.20	5.00	1,000	0.83	0.83
Age 18–44	900	0.15	6.67	500	0.56	0.56
Age 45–64	1,500	0.25	4.00	1,000	0.67	0.67
Age 65+	2,400	0.40	2.50	1,200	0.50	0.50
Region 2	9,000	1.00	—	7,550	0.84	1.38
Age 0–17	3,200	0.36	2.81	2,650	0.83	0.83
Age 18–44	2,900	0.32	3.10	1,500	0.52	0.52
Age 45–64	850	0.09	10.59	2,400	2.82	2.82
Age 65+	2,050	0.23	4.39	2,800	1.37	1.37

We then weight the observed measure of access by the estimated population weight. For example, among enrollees aged 0–17 in Region 1 in the above table, the unweighted average number of visits per enrollee is calculated as 1,000 visits divided by 1,200 enrollees, or 0.83. The weighted number of visits per enrollee is calculated as 1,000 visits multiplied by the population weight (5.00) and divided by the total region population (6,000). When weighted in this way, visits per person in each age group are equally likely to be observed within each region and also between regions.

The total population-weighted number of visits per enrollee (in Region 1, 0.64) is calculated as the simple average of visits per enrollee in each age group. Note that the within age-group visit rates are equal, whether weighted or unweighted; only the population average is changed as a result of re-weighting the age groups to be equally likely in both populations. Whether the regional difference in the populated-weighted averages is meaningful can be assessed by calculating population-weighted variance estimates to test for statistically significant differences (using a z or chi-2 test), from the perspective of clinical significance, or both.

Recall that the weighted values have no real meaning; only the relative values are meaningful. Therefore, we would report the following table:

Ratio of specialist visit rates in Region 1 as a percentage of visit rates in Region 2: Observed versus population-weighted estimates

	Observed (unweighted)	Population-weighted
Region 1 as a percentage of Region 2	73.5%	46.2%

After adjusting for population age differences, we find that utilization per enrollee in Region 1 (where the population is, on average, much older) is about half (46.2% = 0.64/1.38) that in Region 2, compared with the much more equal ratio (73.5% = 0.62/0.84) that we observe without weighting.

Endnotes

[1] U.S. Department of Health and Human Services, Centers for Medicare & Medicaid Services. "42 CFR Part 447. Medicaid Program; Methods for Assuring Access to Covered Medicaid Services. Final Rule." *Federal Register,* vol. 80, no. 211, November 2, 2015, p. 67576.

[2] For example, California reported dental visits among enrollees under age 20 in 7 age groups and 18 regions, producing 126 strata for comparison. See: California's Fee-for-Service Medi-Cal Program Health Care Access Monitoring Plan (September 2016). Available at https://www.medicaid.gov/medicaid/access-to-care/downloads/review-plans/ca-amrp-16.pdf, accessed September 19, 2018.

[3] Ordinary least squares (OLS) regression assumes that the dependent variable is continuous and normally distributed. However, defined as the number of services used, M is lower-bounded by zero and may be skewed (for example, it may have many values of 1, but rarely more). In this case, the analyst would want to use generalized least squares (GLM) estimation instead of OLS, transform the dependent variable to equal log(M) or ln(M), or both. Alternatively, the analyst might define M to be any service used (0 = no; 1 = yes) and estimate a logit model. Major statistical software packages such as SAS or STATA offer these options. Nevertheless, OLS regression is remarkably robust in most applications where the dependent variable is continuous, even if skewed. See: Habeck, Christian, and Adam Brickman. "A Common Statistical Misunderstanding in Psychology and Neuroscience: Do We Need Normally Distributed Independent or Dependent Variables for Linear Regression to Work?" 2018. Available at https://www.biorxiv.org/content/early/2018/04/24/305946, accessed September 19, 2018.

[4] If using Medicaid claims-level data for analysis, the presence of clinically relevant morbidities can be assessed by reviewing the data for key diagnosis codes. Such morbidities might include any diagnosis of a chronic condition or indication of a serious medical problem (for example, pediatric hypertension). Some studies have used a simple count of major comorbidities to represent the burden of illness in the population.

[5] Poor model fit indicates that the model is missing explanatory variables that are independent of those included in the model and might improve the model fit. Missing variables that are related to (or highly correlated with) any of the independent variables specified in the model will contribute (positively or negatively) to the magnitude of the estimated coefficient for that variable.

[6] For a recent example of pooled time-series regression analysis that might be adapted to measure significant changes in regional access, see: Elliott, Marc N., Christopher W. Cohea, William G. Lehrman, Elizabeth H. Goldstein, Paul D. Cleary, Laura A. Giordano, Megan K. Beckett, and Alan M. Zaslavsky. "Accelerating Improvement and Narrowing Gaps: Trends in Patients' Experiences with Hospital Care Reflected in HCAHPS Public Reporting." *Health Services Research,* vol. 50, no. 6, December 2015, pp. 1850–1867.

[7] See: Stuart, Elizabeth A., Sue M. Marcus, Marcela V. Horvitz-Lennon, Robert D. Gibbons, and Sharon-Lise T. Normand. "Using Non-Experimental Data to Estimate Treatment Effects." *Psychiatric Annals,* vol. 39, no. 7, July 1, 2009, pp. 719–728. Available at https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2886294/, accessed September 19, 2018. As with all regression analyses, regression adjustment can lead to biased results when model assumptions (such as a normal error distribution, if using ordinary least squares regression) are violated.

[8] Because we assume that the analyst would have access to administrative data encompassing all Medicaid fee-for-service enrollees, estimation bias is not of concern here (as it would be if the analyst were using data on a population sample).

[9] A simple description of this method is found in the following source: Stuart, Elizabeth A., Sue M. Marcus, Marcela V. Horvitz-Lennon, Robert D. Gibbons, and Sharon-Lise T. Normand." Using Non-Experimental Data to Estimate Treatment Effects." *Psychiatric Annals,* vol. 39, no. 7, July 1, 2009, pp. 719–728. Available at https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2886294/, accessed September 19, 2018.

[10] This method is often used to weight survey samples to known population characteristics, but it can be adapted to adjust for differences in regional population characteristics to enable comparison. See: Izrael, David, David C. Hoaglin, and Michael P. Battaglia. "A SAS Macro for Balancing a Weighted Sample." n.d. Available at http://www2.sas.com/proceedings/sugi25/25/st/25p258.pdf, accessed September 19, 2018.

[11] Examples of raking are found in the health services research literature. For example, see: DeVoe, Jennifer E., Lisa Krois, and Rob Stenger. "Do Children in Rural Areas Still Have Different Access to Health Care? Results from a Statewide Survey of Oregon's Food Stamp Population." *Journal of Rural Health Care Access,* vol. 25, no. 1, winter 2009, pp. 1–7.

[12] The form of the model is most often logistic regression, where the dependent variable is the probability of an individual residing in the region (versus a comparison region), and the independent variables are categorical and/or continuous variables that predict location. The diagnostics for propensity score estimation are not the standard logistic regression diagnostics. Instead, the success of a propensity score model is determined by the balance of measured characteristics that results from the modeling.

[13] For a discussion of propensity-score matching in clinical research, see: Austin, Peter C. "An Introduction to Propensity-Score Methods for Reducing the Effects of Confounding in Observational Studies." *Multivariate Behavioral Research,* vol. 46, no. 3, May 2011, pp. 399–424.

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