



# Medicaid Access Technical Assistance Brief

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## Methods to Identify Changes in Access Among Medicaid Beneficiaries

*This brief presents methods that state Medicaid agencies can use to assess changes in access as part of their AMRPs. Some of the methods are derived from quality improvement, and others are more traditional statistical methods. 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 beneficiaries.*

### A. Introduction

This brief describes several methods that state Medicaid agencies can use to analyze changes in access among Medicaid FFS beneficiaries in their AMRPs. Our goal is to provide general methods for assessing changes in access within Medicaid that states can apply to their specific needs, data sources, and measures. The target audience includes state Medicaid staff who conduct analyses for the AMRPs and senior staff who supervise, and act on the findings of, these analyses.

The applicability of these methods depends in large part on the number of data points that a state has for a measure. Using measures with multiple data points over time allows for stronger analyses and more accurate depictions of trends. Some methods can also be used to identify factors that may have contributed to any changes in access that are observed. The brief also suggests how Medicaid analysts may deal with access measure results at few or only two points in time.

We recognize that resources—including data sources and analytics personnel—vary across states. The methods in this brief are therefore intended for individuals with various levels of statistical expertise to conduct meaningful analyses. We summarize each method, discuss its potential application in the context of AMRPs, and provide examples to help the reader assess the practicality of each method for developing an AMRP.

**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.

### B. Methods from quality improvement

Run charts and control charts are conventionally used in quality improvement efforts to improve processes or systems in health care and other settings, but they can also be used to identify trends and thresholds in state AMRPs. They are easily accessible, practical methods that state staff with a wide range of skills can use to identify trends in access. They do not require statistical training to implement or interpret. Both are used to monitor measures over time and assess whether a desirable change is sustained over time and potentially attributable to a specific intervention. Run charts and control charts also can help users to identify undesirable trends.

#### 1. Run charts

**Definition.** A run chart is a line graph with multiple data points plotted over time with the median as the horizontal line (Figure 1). Run charts are

## ADVANTAGES AND CHALLENGES OF USING RUN CHARTS IN AMRPS

### Advantages

- Simple and straightforward to implement
- Intuitive to interpret
- “Off-the-shelf” tools available to states
- Users with limited training can apply methods by using a basic spreadsheet or statistical software functions
- Can assess random variation or an actual change

### Challenges

- Need multiple data points over time to observe trends
- Interpretation can be subjective
- Cannot determine cause of any observed changes
- Analysis cannot adjust for changes in population characteristics over time
- Cannot determine significance of trends

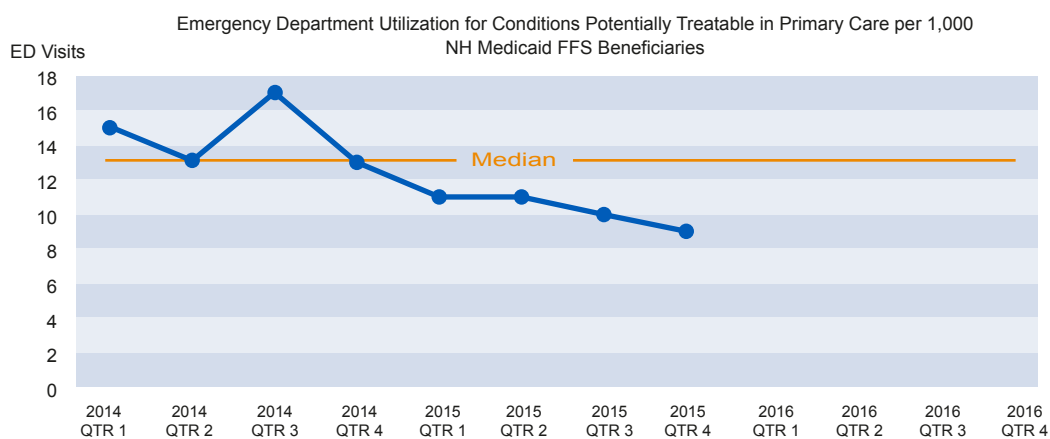
based on the statistical characteristics of time series, but they incorporate rules for interpreting patterns that do not require statistical expertise.<sup>1</sup> For example, it is unlikely that there will be random variation in the data when five or more consecutive points are all going up or down (referred to as a *trend*) or when six or more consecutive points all fall either above or below the median (referred to as a *shift*).<sup>2</sup>

**Resources for implementation.** The Institute for Healthcare Improvement provides a publicly available spreadsheet template that allows users to enter data and construct a run chart.<sup>3</sup> In addition, any statistical package can be used to create a similar figure. At least 10 data points should be plotted to observe meaningful patterns, but

analysts can plot data at the start of data collection and build on the run chart over time.

**State example.** We used data from New Hampshire’s 2016 AMRP on emergency department (ED) use for conditions potentially treatable in primary care (rate per 1,000 Medicaid FFS beneficiaries) to construct an example of a run chart based on IHI’s spreadsheet template (Figure 1). In this example, five consecutive points are going down after the third quarter of 2014, which would be considered a trend and suggest that this is a real decrease in ED use, not random variation. However, it is not clear whether this decrease is large enough to be important or significant to the state.

**Figure 1. Example of a run chart based on New Hampshire’s AMRP data**



Source: New Hampshire Department of Health and Human Services. “Monitoring Access to Care Plan for New Hampshire’s Fee-for-Service Medicaid Medical Services Program.” Appendix B, Figure 24, p. 65. October 2016. Available at <https://www.medicare.gov/medicaid/access-to-care/downloads/review-plans/nh-amrp-16.pdf>. Accessed on April 30, 2018.

## 2. Control charts

Similar to run charts, control charts are plots of multiple data points that show changes over time. Control charts, however, incorporate additional information from the variation in the data that allows users to assess the stability of a measure and determine thresholds at which a change is likely to be important.

**Definition.** Control charts display the mean and the upper and lower limits of historical data, usually defined as three standard deviations from the mean (Figure 2). As in run charts, a set of rules allows users to interpret whether a measure is stable over time or whether it is showing a signifi-

cant trend. Data points within the limits suggest stability (or no real change); in the terminology of quality improvement, this is called *common cause variation*. Data points that are beyond the limits suggest a potentially important change from the baseline; this is called *special cause variation*.<sup>4</sup> The recommended minimum number of data points is 12 for this type of analysis. If there are not enough data points, then the data can be plotted, but the upper and lower control limits must be calculated at a later time when there are enough points.<sup>5</sup> Alternatively, an analyst could use historical data for a measure or plan to generate a measure more frequently. For example, a claims-based measure that was calculated on an annual basis could be calculated on a quarterly basis.

## ADVANTAGES AND CHALLENGES OF USING CONTROL CHARTS IN AMRPS

### Advantages

- Simple and straightforward to implement
- Intuitive to interpret
- “Off-the-shelf” tools available to states
- Analysts with limited training can apply methods by using basic spreadsheet or statistical software functions
- Can assess random variation or an actual change
- Can assess significance of a change

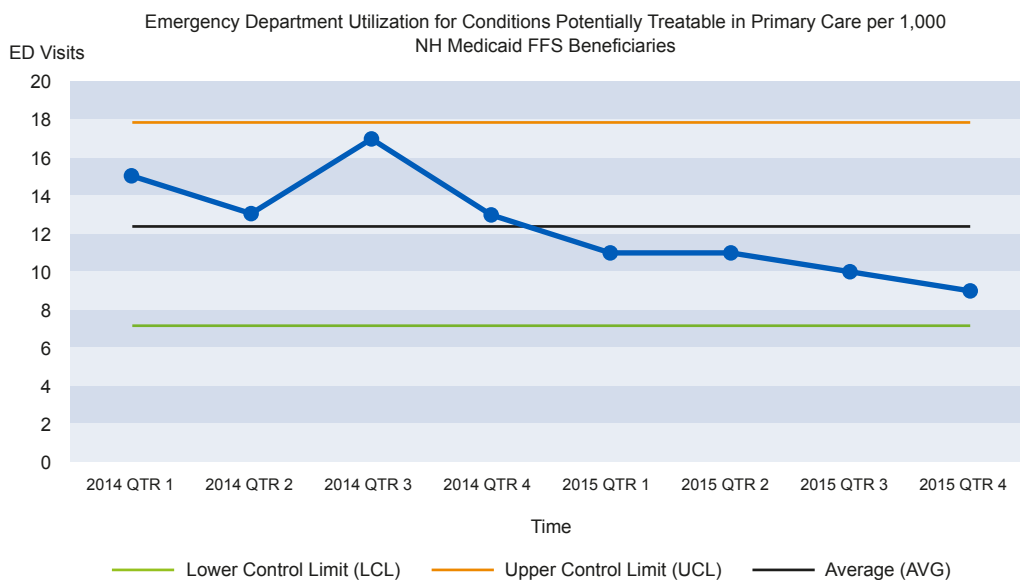
### Challenges

- Need multiple data points over time to observe trends
- Interpretation can be subjective
- Cannot determine cause of any changes observed
- Analysis cannot adjust for changes in population characteristics over time

**Resources for implementation.** Analysts can choose from a range of statistical software to construct control charts.<sup>6,7,8,9,10</sup> The American Society for Quality (ASQ) provides a publicly

available spreadsheet template that automatically calculates the mean and the upper and lower control limits (at three standard deviations from the mean).<sup>11</sup>

**Figure 2. Example of a control chart based on New Hampshire’s AMRP data**



Source: “Monitoring Access to Care Plan for New Hampshire’s Fee-for-Service Medicaid Medical Services Program.” Appendix B, Figure 24, p. 65. October 2016 Available at <https://www.medicaid.gov/medicaid/access-to-care/downloads/review-plans/nh-amrp-16.pdf>. Accessed on April 30, 2018.

Note: The chart shows the average as 12.4 ED visits per 1,000 and the upper control limit (UCL) and lower control limit (LCL) of three standard deviations (17.7 and 7.1, respectively). The changes in the data fall within the limits, suggesting that there were no significant changes, but at least 12 data points would be needed for a stronger conclusion.

**State examples.** We plotted data from New Hampshire’s 2016 AMRP on ED use for conditions potentially treatable in primary care (Figure 2). In this example, the data fluctuate within the limits, implying that the plotted measures fall within the expected range of variability and that the measure is stable. Thus, the changes are not significant enough to note despite the fact that the changes observed in the run chart were a trend. However, given there are fewer than 12 data points, more data should be collected, and limits should be recalculated if we want to observe any significant changes.

California and Pennsylvania included control charts in their 2016 AMRPs (Figure 3).<sup>12</sup> Both states plan to continue to monitor the changes and to investigate any changes that fall outside of the limits.

### C. Time series analysis

Time series analysis is a statistical method that could be used to assess the trend in an access measure. This analysis would work best for access measures that are or that could be frequently available. As with the quality improvement methods, analysts could use historical data for a measure or plan to generate a measure more frequently to support a time series analysis. For example, a claims-based measure that was calculated on an annual basis could be calculated on a quarterly basis. Time series analysis can be used for any type of access measure variable (continuous or categorical).

**Definition.** Time series analysis looks at the patterns of multiple points for the same measure (variable) over time. It is ideal, but not required, to have at least eight observations in the baseline and follow-up periods to have

## ADVANTAGES AND CHALLENGES OF USING TIME SERIES ANALYSES IN AMRPS

### Advantages

- Identifies and forecasts trends
- Easy to present and interpret results in graphs
- Can adjust differences in population characteristics with additional data

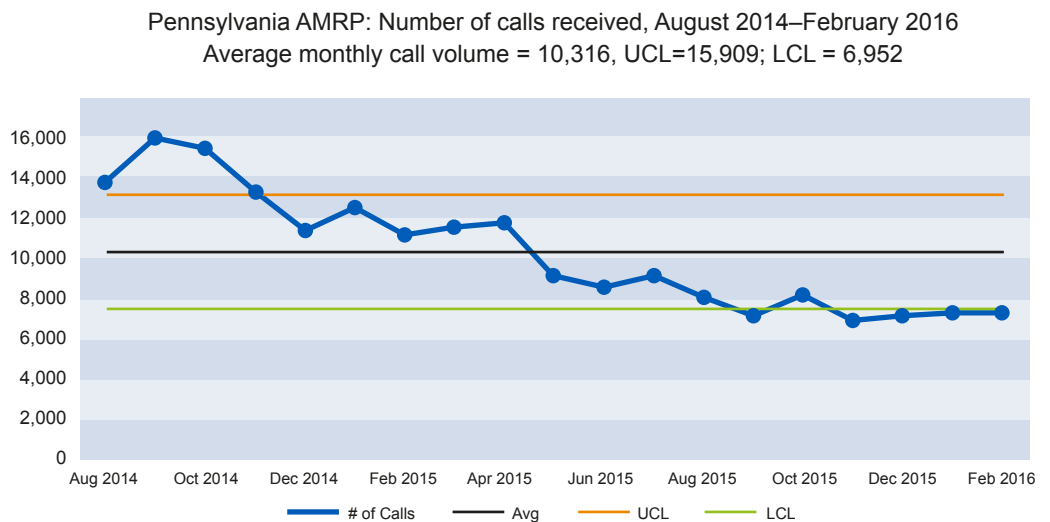
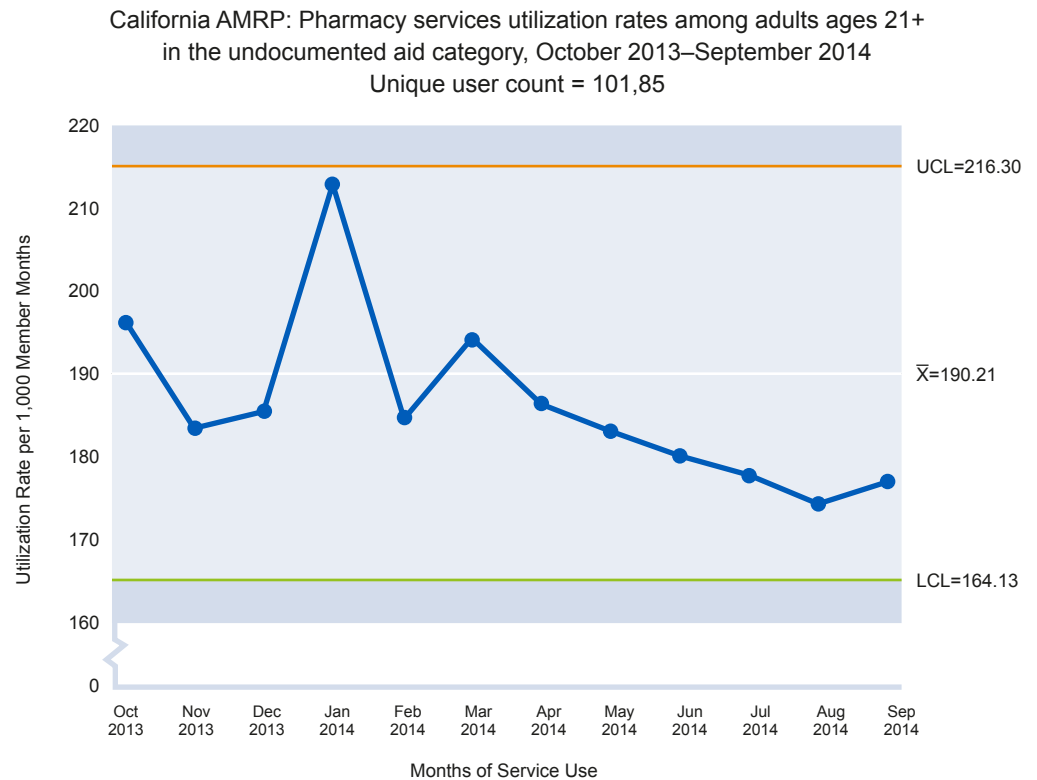
### Challenges

- Requires data from multiple points in time
- Requires high level of statistical expertise
- Need to assess multiple possible causes for any changes observed

enough power for analysis.<sup>13</sup> The methods that can be used for time series analysis can account for important features of time series patterns. These more technical methods require a higher level of statistical expertise.<sup>14</sup>

**Resources for implementation.** Analysts can use any statistical software package to conduct a time series analysis and graph the results.<sup>15,16,17,18,19</sup>

**Figure 3. Examples of control charts in California and Pennsylvania's 2016 AMRPs**

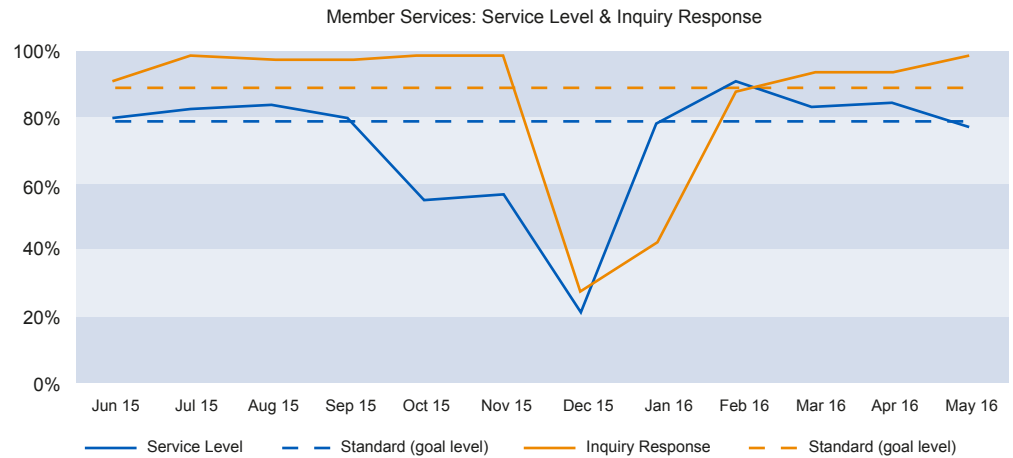


Sources: The California Department of Health Care Services. "California's Fee-for-Service Medi-Cal Program Health Care Access Monitoring Plan." September 2016, p. 70; and the Pennsylvania Department of Human Services. "Pennsylvania Access Monitoring Review Plan 2016." Figure 2, p.9. Available at <https://www.medicaid.gov/medicaid/access-to-care/review-plans/index.html>. Accessed April 30, 2018.

**State example.** In its 2016 AMRP, Iowa Medicaid reported beneficiaries' call-center data from June 2015 to May 2016 and displayed these data in a time series graph showing the changes in

the center's responsiveness to FFS members' calls and inquires compared to contractual expectations (Figure 4).

**Figure 4. Example of time series graph from Iowa's AMRP**



Source: Iowa Department of Human Services. "Access Monitoring Review Plan 2016." October 2016, p. 4. Available at <https://www.medicaid.gov/medicaid/access-to-care/downloads/review-plans/ia-amrp-16.pdf>. Accessed April 30, 2018.

#### D. Methods for analyzing access measures with few data points

In many situations, analysts will have data for an access measure at few or only two points in time. For example, for the 2019 AMRP, a state Medicaid agency might compare results for a measure of clinician acceptance of Medicaid patients from a survey in 2018 with results for the same measure reported in the 2016 AMRP. These are often referred to as before-and-after or pre-post analyses.

**Definition.** Pre-post analyses compare values for the same measure and for the same population at two

points in time. For the purposes of state analyses for AMRPs, the population consists of Medicaid FFS beneficiaries for whom a measure is relevant.

**Resources for implementation.** There are many statistical tests available to assess significant differences between time points, and an analyst should choose a statistical test according to the type of variable produced by the access measure (Table 1).<sup>20</sup> For example, an ED visit rate could be defined as a continuous variable (for example, the mean number of visits per 1,000 beneficiaries in the prior 12 months), or as a categorical variable (for example,

**Table 1. Examples of access measures and statistical test option**

| Measure   | AMRP domain <sup>a</sup> | Potential data source            | Type of variable  | Statistical tests   |
|---|--------------------------|----------------------------------|---|---|
| Rate of potentially avoidable ED visits   | Utilization              | All-payer claims database        | Continuous (for example, mean number of ED visits per 1,000 individuals)    | t-test, analysis of variance (ANOVA), regression analysis |
| Proportion of providers accepting new patients with Medicaid versus other health coverage | Availability of care     | Provider survey                  | Categorical (for example, provider accepts or does not accept new patients) | Chi-square, logistic regression                           |
| Proportion of beneficiaries with unmet health care needs                                  | Beneficiary needs        | General population health survey | Ordinal (for example, zero, one, or more than one unmet need)               | Chi-square, ordered logistic regression                   |

<sup>a</sup> In the AMRPs, states were required to include measures of access to care in three domains: (1) beneficiary health needs and whether they are adequately met, (2) the availability of care and providers, and (3) changes in beneficiaries' utilization of covered services over time.

## ADVANTAGES AND CHALLENGES OF USING PRE-POST ANALYSES IN AMRPS

### Advantages

- Relatively easy to implement with basic statistical knowledge
- Good for short-term assessments of change
- Can adjust for differences in population characteristics with additional data

### Challenges

- Comparing two points in time is limited in describing the overall trend
- Cannot determine the causes of any changes observed
- Trends from comparison groups are not incorporated

the proportion of beneficiaries with any ED visit in the prior 12 months). When analyzing a continuous variable, an analyst could use a paired or unpaired t-test to assess whether any difference between a baseline and follow-up value was statistically significant. Similarly, when analyzing a categorical variable, an analyst could use the chi-squared test. Analysts can use any statistical software—such as SAS, SPSS, STATA, and R—to conduct these analyses.<sup>21,22,23,24</sup> Microsoft Excel also has a data analysis function.

In many cases, changes in the characteristics of Medicaid beneficiaries could confound the interpretation of results that show a difference (or no difference) in access between two points in time. For example, changes in the age composition of Medicaid beneficiaries could contribute to rates of ED use. If data are available, an analyst can use a multivariate regression model to control for confounding factors that could influence the interpretation of the comparison. There are a number of regression techniques

available for different types of variables. Regression analysis can be complex and requires a level of understanding on the type of data and assumptions of the regression model data. Analysts and other staff who are not familiar with regression analysis should explore the type of analysis that best fits the available data and consult with statistical experts.

**State example.** We used a spreadsheet to conduct a paired t-test comparing values reported by New Hampshire in its AMRP for a measure of ED use for conditions potentially treatable in primary care in 2014 and 2015 (Figure 5). We selected the paired t-test based on the assumption that the enrolled population in 2014 was largely the same as the enrolled population in 2015. If this assumption was unlikely to be accurate, an unpaired t-test should be used. The decline from 2014 to 2015 was statistically significant ( $p$ -value < 0.05).

**Figure 5. Example of a comparison of ED visits for conditions potentially treatable in primary care in 2014 and 2015 from New Hampshire's 2016 AMRP**

|    | A    | B    | C | D                                   | E           | F           |
|----|------|------|---|-------------------------------------|-------------|-------------|
| 1  | 2014 | 2015 |   |                                     |             |             |
| 2  | 15   | 11   |   |                                     |             |             |
| 3  | 13   | 11   |   |                                     |             |             |
| 4  | 17   | 10   |   |                                     |             |             |
| 5  | 13   | 9    |   |                                     |             |             |
| 6  |      |      |   | t-Test: Paired Two Sample for Means |             |             |
| 7  |      |      |   |                                     |             |             |
| 8  |      |      |   |                                     | 2014        | 2015        |
| 9  |      |      |   | Mean                                | 14.5        | 10.25       |
| 10 |      |      |   | Variance                            | 3.666666667 | 0.916666667 |
| 11 |      |      |   | Observations                        | 4           | 4           |
| 12 |      |      |   | Pearson Correlation                 | 0.090909091 |             |
| 13 |      |      |   | Hypothesized Mean Difference        | 0           |             |
| 14 |      |      |   | df                                  | 3           |             |
| 15 |      |      |   | t Stat                              | 4.123105626 |             |
| 16 |      |      |   | P(T<=t) one-tail                    | 0.012932292 |             |
| 17 |      |      |   | t Critical one-tail                 | 2.353363435 |             |
| 18 |      |      |   | P(T<=t) two-tail                    | 0.025864584 |             |
| 19 |      |      |   | t Critical two-tail                 | 3.182446305 |             |

Source: "Monitoring Access to Care Plan for New Hampshire's Fee-for-Service Medicaid Medical Services Program." Appendix B, Figure 24, p. 65. October 2016. Available at <https://www.medicaid.gov/medicaid/access-to-care/downloads/review-plans/nh-amrp-16.pdf>. Accessed on April 30, 2018.

## E. Discussion

By selecting the right data and the appropriate analysis method, states can conduct meaningful analyses of data and trends to evaluate access to care for covered services. The choice of one method over another is driven by the data available and the statistical expertise on or available to the team conducting the analyses for the AMRP. Although more data points always

contribute to a stronger analysis, the methods outlined in this brief illustrate that informative analyses can be conducted with varying numbers of observations and levels of statistical expertise. By using these methods and by thoughtfully interpreting and presenting the results, state staff can provide valuable information to experts and policymakers about access to care for the Medicaid FFS population over time.



## Endnotes

- <sup>1</sup> Perla, R.J., L.P. Provost, and S.K. Murray. "The Run Chart: A Simple Analytical Tool for Learning from Variation in Healthcare Processes." *BMJ Quality & Safety*, vol. 20, 2011, pp. 46-51. Available at <http://www.med.unc.edu/ccf/files/education-training/The%20run%20chart%20a%20simple%20analytical%20tool.pdf>. Accessed May 2, 2018.
- <sup>2</sup> See Perla, R.J., L.P. Provost, and S.K. Murray (2011) for tabular critical values to determine too many and too few runs.
- <sup>3</sup> Institute for Healthcare Improvement. "Run Chart Tool." Available at <http://www.ihf.org/resources/Pages/Tools/RunChart.aspx>. Accessed April 30, 2018.
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- <sup>5</sup> Sherman, P.J. "Smart Charting." Available at <http://asq.org/quality-progress/2012/07/back-to-basics/smart-charting.html>. Accessed May 24, 2018.
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- <sup>7</sup> "Data Analysis and Statistical Control." Available at <http://faculty.washington.edu/htamura/qm500/king/Ch02.pdf>. Accessed on April 30, 2018.
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- <sup>9</sup> Anhoej, J. "Control Charts with Qicharts for R." Available at <https://cran.r-project.org/web/packages/qicharts/vignettes/controlcharts.html>. Accessed April 30, 2018.
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- <sup>11</sup> The American Society for Quality. "Control Chart." Available at <http://asq.org/learn-about-quality/data-collection-analysis-tools/overview/control-chart.html>. Accessed April 30, 2018.
- <sup>12</sup> Pennsylvania did not refer to the chart in their AMRP as a control chart, but it contains the elements of a control chart (for example, multiple data points over time, mean, and standard deviation lines).
- <sup>13</sup> Rozario, N.L., C.G. Moore, and A. McWilliams. "Interrupted Time Series Power Calculation Using DO Loop Simulations." Available at: <http://support.sas.com/resources/papers/proceedings17/1339-2017.pdf>. Accessed May 24, 2018.
- <sup>14</sup> State of Oregon Department of Environmental Quality. "Trend Analysis and Presentation." Available at <http://www.oregon.gov/deq/FilterDocs/TrendAnalysisCD.pdf>. Accessed May 2, 2018.
- <sup>15</sup> Brocklebank, J.C., and D.A. Dickey. "Overview of Time Series." In *SAS for Forecasting Time Series*. Second Edition. Cary, NC: SAS Institute and Wiley, 2003, pp. 1-26. 2003. Available at [https://www.sas.com/storefront/aux/en/spforetime-series/57275\\_excerpt.pdf](https://www.sas.com/storefront/aux/en/spforetime-series/57275_excerpt.pdf). Accessed April 30, 2018.
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- <sup>24</sup> Spector, P. "Using T-Tests in R." Available at <https://statistics.berkeley.edu/computing/r-t-tests>. Accessed April 30, 2018.