IES Institute of Education Sciences

Analyzing Teacher Mobility and Retention: Guidance and Considerations Report 2

Analyzing Teacher Mobility and Retention: Guidance and Considerations Report 2

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This applied research methods report is a guide for state and local education agency policymakers and their analysts who are interested in studying teacher mobility and retention. This report is the second in a two-part set and builds on the foundational information in report 1. This report presents guidance on how to interpret differences in mobility and retention rates by teacher, school, or district characteristics; analyze year-to-year trends in mobility and retention; compare mobility and retention rates across districts or states; and examine how the implementation of a policy related to teachers might be associated with teacher mobility or retention.

CONTENTS

WHY THIS REPORT?

This report presents guidance on how to examine teacher mobility and retention rates to address a range of objectives and how to support stakeholders in interpreting and using the information for policy decisions. Specifically, this report covers:

- Interpreting differences in mobility and retention rates by teacher, school, or district characteristics.

- Analyzing year-to-year trends in mobility and retention.

- Comparing mobility and retention across districts or states.

- Examining how the implementation of a state or district policy related to teachers might be associated with teacher mobility or retention.

This is the second of a two-report set called *Analyzing Teacher Mobility and Retention: Guidance and Considerations.* It builds on the first report, which provides state and local education agency policymakers and other education stakeholders with the foundational information needed to analyze teacher mobility and retention.

Before reading this report, readers might find it useful to read report 1. Those who are familiar with calculating mobility and retention rates might opt to begin with this report, which provides more detailed guidance on answering teacher mobility and retention research questions.

State and local education agency data analysts can use this report as a guide for undertaking analyses that meet these objectives. In turn, the analysts can work with policymakers in interpreting and using the results for policy decisions. See box 1 for definitions of key terms used in the report.

This report explains the process of conducting the above analyses in a manner easily accessible to nonanalysts. For each type of analysis, there are a description of what to consider, hypothetical examples, and a box with a more detailed sample analysis using information from one or more of the three scenarios introduced in report 1 and described in box 2 below. The three scenarios are realistic hypothetical examples informed by more than two dozen studies on teacher mobility and retention. The hypothetical information in these scenarios was drawn from Regional Educational Laboratory publications and other widely cited, peer-reviewed research journals from the past 15 years.[1] In all these studies the key outcome is mobility or retention, and the focus is teachers rather than administrators.

The guidance in this report is not solely for data analysts but for a multidisciplinary stakeholder team of policymakers, program managers, data managers, and data analysts. Individuals without a background in research or data analysis might find this report useful for improving communication with data managers or analysts. The report might also improve understanding of analysis decisions and their implications—policy and other—on the results. However, carrying out several of the steps will require someone with data analysis experience. So it is advisable to work in teams and involve staff with data analysis experience.

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1. Appendix B in report 1 presents a matrix of the studies that informed the report set, indicating the data elements, such as educator and school-level variables, used in each report. Appendix D in report 1 provides a summary of each study.

Box 1. Key terms

The following definitions of key terms are presented as a quick reference only. There are variety of ways in which these simple definitions might not be sufficient—for example, what to call teachers who change roles or take a temporary leave. For a thorough discussion of the nuances of these terms, see report 1.

- **Attrition rate.** The percentage of teachers who are leavers.
- **Leavers.** Teachers who left their initial administrative unit in a given timeframe and did not enter another administrative unit during that timeframe.
- **Mobility rate.** The percentage of teachers who are movers.
- **Movers.** Teachers who moved from their initial administrative unit to a different administrative unit in a given timeframe. The administrative unit that determines whether a teacher is a mover might differ from the one used to determine whether a teacher is a leaver. For example, a mover might be defined as a teacher who moves between schools within a state, whereas a leaver might be defined as a teacher who is no longer teaching in the state.
- **Retention rate.** The percentage of teachers who are stayers.
- **Stayers.** Teachers who remained teaching in at least one of their initial administrative units in a given timeframe. For example, a teacher who splits time between two schools might be defined as a stayer if the teacher remains in one of the schools.
- **Trend plot.** A visual display of data over time. Also called a line graph. Each data point is plotted on a chart where the horizontal axis represents time and the vertical axis represents frequency counts or percentages.

Box 2. Example scenarios and additional research questions

The following three scenarios represent common analyses that state and local departments of education might undertake. These scenarios were introduced in report 1, which detailed how mobility and retention rates could be calculated to answer research questions. In the current report these same scenarios are used to illustrate how the answer to those original research questions often leads to additional research questions and how State and local education agency data can approach solving those new research questions. This process could continue iteratively, such that the answer to a new set of research questions leads to yet another set of research questions.

Scenario 1: Mobility and retention among beginning teachers
Stakeholders from a small state (State A) want to understand the extent to which beginning teachers who completed a teacher preparation program in the state are moving between schools, staying in their initial school, and leaving teaching positions in the state public school system. The stakeholders articulated their original research question as:

- What percentages of beginning teachers prepared in State A move to another school, stay in their school, and leave teaching in State A public schools?

The analyst calculated retention and mobility rates for State A following the process outlined in report 1 and then held a meeting to share the results with the stakeholders. During the meeting the state stakeholders express interest in examining the patterns of mobility and retention by teacher and school characteristics, such as whether teachers with certain certifications or in high-need schools are leaving at higher

rates. The state stakeholders are also interested in whether differences exist between beginning teachers prepared in State A and beginning teachers prepared out-of-state. The state stakeholders also express interest in whether a relationship exists between teacher participation in the state's mentoring program and retention, because they are aware that some teachers participate with more fidelity than others. At the end of the meeting, the analyst and the stakeholders agree on the following two new research questions:

- Do patterns of mobility, retention, and attrition rates among beginning teachers vary by teacher characteristics (such as certification type or in-state versus out-of-state preparation) and school characteristics (such as high- or non-high-needs schools)?
- Is there a relationship between retention of beginning teachers and the fidelity with which they participated in the state's mentoring program?

Scenario 2: Mobility and retention in high-need schools

Board of education members in a large urban district in State B have heard anecdotal reports that teachers are leaving high-need schools at higher rates than they are leaving more affluent schools in the district. The board members asked the district's data analyst to investigate the issue. The stakeholders articulated their original research questions as:

- What are the teacher mobility and retention rates in District 1 for the past five years?
- How do the rates compare between teachers in high-need and teachers in non-high-need schools?

The analyst calculated the three-year retention rate for each school in District 1 for the past five years as well as the in-district retention and mobility rates for the entire district for the past five years. The analyst communicates these findings, which pertain to the first research question, to the board members in the interim report and confirms that the board is still interested in comparing high-need and non-high-need schools, the second research question.

Scenario 3: Relationship between the institution where a teacher is prepared and teacher retention

Postsecondary and secondary school policymakers in a populous state (State C) are collaborating to better understand how teachers' preservice experience is related to their retention. The policymakers are particularly interested in whether teachers from the state's public institutions of higher education have higher retention rates than teachers from private institutions. The policymakers articulated their original research question as:

- Is there a relationship between the type of institution (public or private) where a teacher is prepared in State C and that teacher's likelihood of staying in or leaving the State C public school system?

After conducting an analysis to answer this question, the analyst informed the policymakers that teachers prepared in private institutions have higher retention rates. After hearing this result, the policymakers ask the analyst why that might be the case. The analyst and policymakers then generate a new research question:

- What factors might explain the observed difference in retention between teachers prepared in public institutions and teachers prepared in private institutions?

ANALYSIS STEPS

Report 1 addressed the initial steps for conducting teacher mobility and retention research. Those steps include stating research questions, determining administrative units and time-frames, defining mobility and retention, determining data requirements, preparing data, and calculating rates.

Report 2 presents four additional steps that state or local education agency staff members can undertake to further examine the mobility and retention rates calculated in report 1. Following these steps will yield information for making evidence-based decisions:

- Step 1: Determine analysis method and data needed to address additional research questions.

- Step 2: Prepare data for analysis.

- Step 3: Produce frequencies and other descriptive statistics.

- Step 4: Examine relationships using regression models.

Although a data analyst will typically perform steps 1–4, getting input from individuals with contextual knowledge of the policies in place that influence teacher mobility and retention can be beneficial. A collaborative approach helps ensure that the data analyst investigates the most useful research questions and that the results are accurate. The results should be discussed with the multidisciplinary team of staff members to interpret their meaning and discern their implications.

Step 1. Determine analysis method and data needed to address additional research questions

Step 1 focuses on deciding how to address additional research questions on mobility and retention rates that emerge from initial results. This process begins where step 6 in report 1 leaves off—after stakeholders have basic mobility and retention rates and have discussed the implications of the results. That discussion is likely to lead to new or updated research questions (see box 2) for which the data analyst will determine whether additional data are needed. For example, if stakeholders want to examine whether mobility and retention rates vary by certain teacher and school characteristics, the analyst will need to check whether those characteristics are included in the data files used to calculate the mobility and reten-tion rates. If they are not, the analyst will need to add those variables to the data files, fol-lowing the procedures outlined in step 5 in report 1.

Next, the analyst will select an appropriate analysis method for addressing the research questions, often choosing between a simple descriptive summary statistical analysis and

an advanced statistical analysis. Questions that concern simple differences in mobility and retention rates by school characteristics can be examined descriptively by simply disaggregating the rates by the school characteristic categories, such as socioeconomic status and locale. Other questions might require more advanced statistical analyses, such as regression analyses, to identify associations between variables such as teacher mobility rates and school locale. An in-depth discussion of situations that might require regression analyses is in step 4.

The choice of analysis method is a complex matter, and it is common for analysts to rely on multiple analysis methods to answer a research question. For example, "Are teachers in rural districts more likely to leave the district than teachers in urban districts?" could be answered in multiple ways.

One analyst might employ simple descriptive summary statistics at the district level, using district retention rates and calculating the mean retention rate separately for rural and for urban districts. The analyst might calculate simple means or weighted means using district enrollment. Whereas simple means would give equal weight to a small district and a large district, weighting by enrollment would give more weight to a large district. The choice between the two should be guided by both the research question and the discussion between the analyst and other stakeholders. Simple means are easy to calculate and communicate but are susceptible to biases from extreme values. For example, smaller districts are more likely than larger districts to have extreme mobility and retention rates due to their smaller sample sizes.[2] If a concern exists regarding small districts biasing the results for the entire state, the analyst might advise stakeholders of the merit of weighted means, despite their complexities.

Another analyst, however, might take a different approach. Instead of calculating a district-level retention rate, the analyst might use teacher-level frequency data on the number of leavers and stayers for each district. The analyst might then total the number of leavers and stayers separately for urban and rural districts, while keeping the administrative unit as the individual district. These totals could be summarized in a two-by-two cross-tabulation, where the rows are "urban" and "rural" and the columns are "stayers" and "leavers" (table 1). The analyst might add a statistical test of association, such as a chi-square test, to this descriptive summary to see whether the relative frequency of stayers and leavers differs significantly between urban and rural districts.

Table 1. Example cross-tabulation of stayers and leavers by district locale

Locale	Stayers	Leavers
Urban district	Total count of stayers in the urban district	Total count of leavers in the urban district
Rural district	Total count of stayers in the rural district	Total count of leavers in the rural district

Source: Authors' creation.

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2. For example, a small district with only 1 beginning teacher will have a retention rate of 100 percent or 0 percent, depending on the movement of this single teacher, whereas a large district with 50 beginning teachers will rarely have such an extreme retention rate.

The choice of analysis method often reflects the data available and the analyst's personal preferences. In the above example the second approach would not be feasible if the analyst had access to data on district retention rates but not to data on the frequencies of stayers and leavers.

As these examples illustrate, there is no clear-cut way to determine the most effective analysis method. In fact, the question in the example could also be analyzed using more sophisticated approaches, including linear regression, logistic regression, and survival analysis. But some analysis methods are more appropriate than others, depending on the type and nature of available data. Nonresearchers such as policymakers and program managers have important roles in advising data analysts, by communicating what outcomes (dependent variables) and predictors (independent variables) they are interested in. Data managers' role is then to inform the analysts which outcomes and predictors are available and what their quality, completeness (missingness), and form (for example, categorical, ordinal, or interval) are. The analyst will take those pieces of information, along with additional considerations such as whether the data are from matched groups or reflect independent groups, to decide on a proper analysis method. Several existing resources describe these terms and their differences and how to choose an appropriate analysis method.[3]

One important consideration when determining the best analysis method is whether simple descriptive summary statistics will suffice as opposed to sophisticated, and potentially complicated, advanced statistics. In general, advanced statistics, such as regression analyses and other inferential statistical methods, are better suited when the research question aims to uncover a complex relationship in the data. However, advanced statistics can be difficult to interpret and explain to a general audience, which could cause unnecessary confusion and delay in policy decisionmaking.

One approach is to perform a simple analysis whose results are communicated to a wide audience and to perform a more sophisticated alternative to verify that claim. If the more sophisticated analysis corroborates the results of the simpler analysis, the simpler analysis could be used for presentations or reports, and the more sophisticated analysis could be placed in an appendix as a technical reference. In some cases the purpose of the analysis demands the more sophisticated alternative. For example, regression analysis is needed to predict retention based on teacher or school characteristics. But if the goal is simply to describe the relationship between retention and a few teacher or school characteristics, a descriptive summary, such as cross-tabulations with a chi-square test of association, would suffice (box 3).

Once the analysis method has been chosen and additional data needs have been identified, the analyst prepares the data file, following the considerations discussed in report 1.

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3. For example, Loeb et al. (2017, available at https://ies.ed.gov/ncee/pubs/20174023/pdf/20174023.pdf) and the Institute for Digital Research and Education's Statistical Consulting site (https://stats.idre.ucla.edu/other/mult-pkg/whatstat/).

Box 3. Analysis methods for the example scenarios

This box describes options for analysis methods for each example scenario. Detailed discussions of the analysis methods and visual displays are presented later in the report.

Scenario 1: Mobility and retention among beginning teachers

State A stakeholders want to understand the extent to which beginning teachers in the state are moving between schools, staying in their initial school, and leaving the profession and whether the results show patterns by teacher and school characteristics. They also want to know whether there is a relationship between teacher participation in the state's mentoring program and retention, because they are aware that some teachers participate with more fidelity than others.

To answer the first question, the analyst examines mobility and retention disaggregated by teacher and school characteristics. Using cross-tabulations, the analyst produces frequencies of the number of movers, stayers, and leavers by teacher and school characteristics. Then, to compare mobility, retention and attrition rates across groups, the analyst computes means for each subgroup and summarizes them in bar graphs. Both cross-tabulations and comparisons of means permit simple tests of statistical significance: a chi-square test of association for cross-tabulations and a t-test for comparisons of means.

To answer the second question about relationships, the analyst uses regression analysis. Because the outcome variable is binary (retained or not retained), logistic regression is performed. Using a logistic regression model enables the stakeholders to understand the relationship between an individual teacher's fidelity of implementation and that teacher's likelihood of retention, after other factors are controlled for.

Scenario 2: Mobility and retention in high-need schools

Board of education members in District 1 in State B have heard anecdotal reports that teachers are leaving high-need schools at higher rates than they are leaving more affluent schools in the district. The board members have asked the district's data analyst to examine annual teacher mobility and retention rates for the past five years and to compare the trends in those rates among teachers in high-need schools and among teachers in non-high-need schools.

The analyst performs a visual examination of five-year trends, disaggregated by high-need schools and non-high-need schools. The analyst creates a line chart with two trend plots, one representing the mean retention rate for high-need schools and the other representing the mean retention rate for non-high-need schools.

Scenario 3: Relationship between the institution where a teacher is prepared and teacher retention

Postsecondary and secondary school policymakers in State C are collaborating to better understand how teachers' preservice experience is related to their retention. The policymakers are particularly interested in whether teachers from the state's public institutions of higher education have higher retention rates than teachers from private institutions.

The analyst examines retention disaggregated by teacher characteristics. Because this concerns individual teachers' characteristics, the analyst analyzes frequency of cases using cross-tabulations. The analyst then follows this up with a chi-square test of association.

The analyst then reports back to the policymakers that teachers prepared in private institutions have higher retention rates. This leads the policymakers to ask why. The analyst wonders whether the observed difference might disappear when other factors are taken into consideration—in other words, when other factors are statistically controlled for. The analyst concludes that the appropriate analytic method is a logistic regression with covariates.

Step 2. Prepare data for analysis

Step 2 involves preparing the data file for analysis and expanding it as needed. If teacher, school, or district characteristics were not part of the first file created but are needed so that the research questions can be addressed, they will be merged into the data file in this step. For a review of how to merge files, see step 5 in report 1.

Ensuring consistency

When an analytic data file is compiled by merging mobility and retention data files for different years or different states, it is important to check for consistency in the definitions of the mobility and retention variables and in the coding structure for those variables. Answering research questions using mobility and retention rates, which were calculated through the process outlined in report 1, often involves combining mobility and retention data for different years or different states. That makes ensuring consistency especially important. As report 1 discusses in detail, there are multiple ways in which these terms can be defined and thus calculated. If the data files to be merged are not consistent in their definitions or calculations of mobility and retention variables, the analyst is advised to decide on the preferred or most relevant definition and calculation and to apply it to each file prior to merging. The analyst might need to consult with the multidisciplinary team to decide on the preferred definition and calculation to apply across files.

Step 3. Produce frequencies and other descriptive statistics

Step 3 describes how to produce frequencies and other descriptive statistics for three common purposes: to examine differences in mobility and retention rates by teacher, school, or district characteristics; to create visual displays of year-to-year trends in mobility and retention; and to compare mobility and retention rates across districts or states.

Examining differences in mobility and retention rates by teacher, school, or district characteristics

There are two primary approaches to help stakeholders understand differences in mobility and retention rates that are disaggregated by teacher, school, and district characteristics: calculating means to compare rates and producing cross-tabulations to compare frequencies. For the comparison of mean mobility and retention rates, the mean is calculated for each subgroup defined by the characteristics. For example, if the research question asks about retention rates by schools in large versus small districts, in place of the overall mean for the three-year retention rate of beginning teachers, the analyst would calculate retention rates separately for schools in large districts and for schools in small districts. The result of that analysis could be summarized as a table or as bar graphs for visual analysis, as in figure 1.

Figure 1. The mean three-year retention rate was higher for small districts than for large districts, 2012/13–2014/15
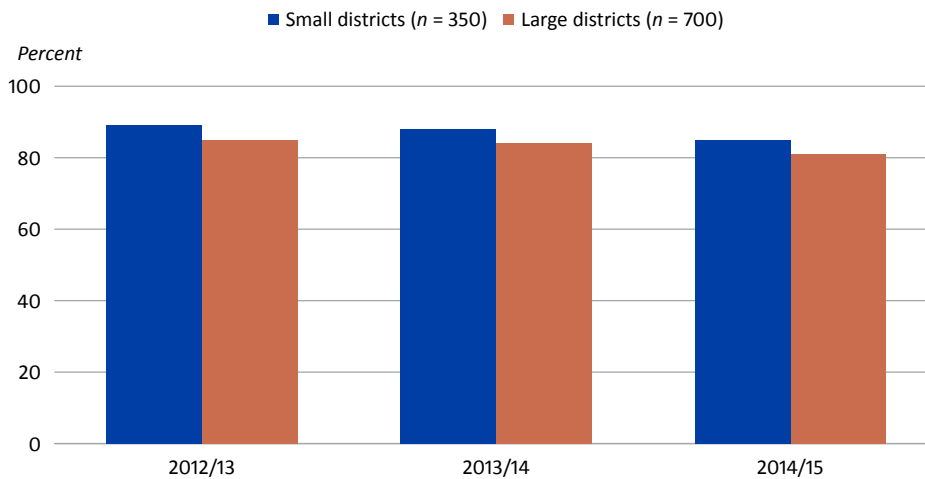
Source: Hypothetical data used for illustration purposes.

When the disaggregation is conducted using frequency data—in other words, on the number of stayers, movers, and leavers—a common approach is to use cross-tabulation. In cross-tabulations each row represents a mutually exclusive category of teachers—for example, stayer, mover, and leaver. Each column represents a mutually exclusive subgroup based on the characteristic of interest—for example, teachers from large districts and teachers from small districts. The cells at each intersection of rows and columns contain the count or frequency of cases, which is teachers in this example (table 2).

Table 2. Three-year teacher retention and attrition rates by district size, 2012/13–2014/15

	Large districts		Small districts		
	Number	Percent	Number	Percent	Row total
Stayers (retention)	2,050	84	4,000	88	6,050
Leavers (attrition)	400	16	550	12	950
Column total	2,450	100	4,550	100	7,000

Source: Hypothetical data used for illustration purposes.

Box 4 shows how data are disaggregated by various characteristics in example scenario 3. Box 5 discusses the process of conducting a visual analysis of trends in mobility and retention in example scenario 2.

Box 4. Disaggregating by teacher characteristics in example scenario 3

Postsecondary and secondary school policymakers in State C are interested in whether teachers from the state's public institutions of higher education have higher retention than teachers from private institutions. To examine retention disaggregated by the type of institution from which individual teachers received their degree, the analyst examines the frequency of cases using cross-tabulations. The analyst and the policymakers then agree to use the latest figure for five-year retention in the state public school system, which comes from the 2015 cohort of beginning teachers.

To create a two-by-two cross-tabulation of (stayer, leaver) x (private, public), the analyst classifies all teachers in the 2015 cohort into four groups: stayer, graduated from private institution; stayer, graduated from public institution; leaver, graduated from private institution; and leaver, graduated from public institution. The analyst then enters the number of teachers in each category in the corresponding cell in the cross-tabulation and calculates the row, column, and grand totals (see table). Finally, the analyst calculates row and column percentages for each cell. After examining the cross-tabulation, the analyst concludes that teachers trained in private institutions have higher five-year retention rates than teachers trained in public institutions.

Example cross-tabulation of stayers and leavers by institution type

| Institution type	Stayers		Leavers		Row total
	Number	Percent	Number	Percent	
Private	A	A / (A + C)	C	C / (A + C)	A + C
Public	B	B / (B + D)	D	D / (B + D)	B + D
Column total	A + B	(A + B) / (A + B + C + D)	C + D	(C + D) / (A + B + C + D)	A + B + C + D

Box 5. Visual analysis of trends in mobility and retention in example scenario 2

Board of education members in District 1 in State B and their analyst have defined retention and mobility in the city as follows: stayers are teachers and school administrators who are in their original school of assignment after three years, movers are teachers and school administrators who are in a different school in the district from their original school of assignment after three years, and leavers are teachers and school administrators who leave public schools in the district within three years.

To analyze the five-year trend in school retention, the three-year retention rate for each of the five years is calculated for the district as a whole. This results in the trend plot of stayers. To provide context, the analyst also adds the trend plot for the entire state. Because the stakeholders are interested in comparing the retention rate of high-need schools with that of non-high-need schools, the analyst adds two more trend plots, disaggregating the three-year retention rate for high-need schools and non-high-need schools (see figure).

The analyst follows the same procedure to create the five-year trend plots for the mobility rate in the district, which results in the trend plot of movers. The analyst then creates the five-year trend plots for the retention rate in the district, which is the sum of stayers and movers. (Alternatively, the analyst could count the number of leavers to create five-year trend plots for the district attrition rate.) In addition to the three trend plots of retention and mobility rates, the analyst also creates a trend plot for the annual frequency of mobility in the district. The analyst adds a trend plot for each of the four types of mobility: move from high-need to non-high-need school, move from high-need to high-need school, move from non-high-need to non-high-need school, and move from non-high-need to high-need school. This plot is used to study the pattern of mobility between high-need and non-high-need schools.

The three-year teacher retention rate is consistently lower in high-need schools than in non-high-need schools
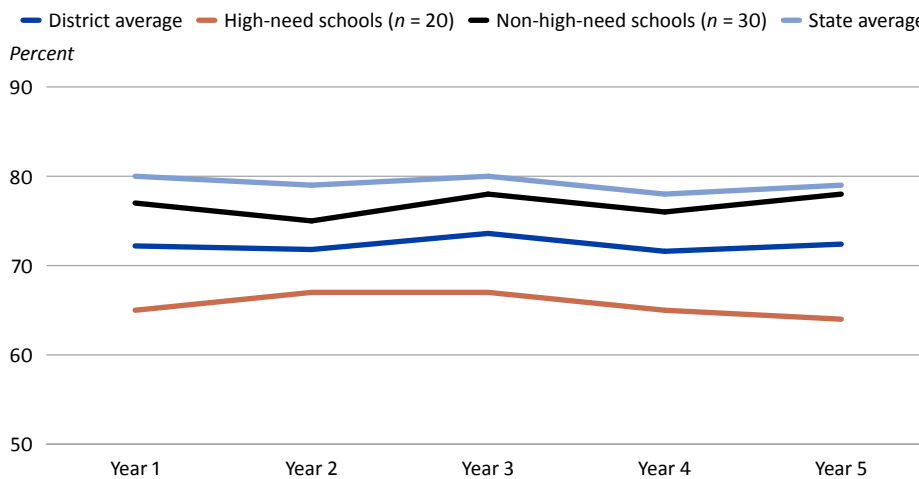
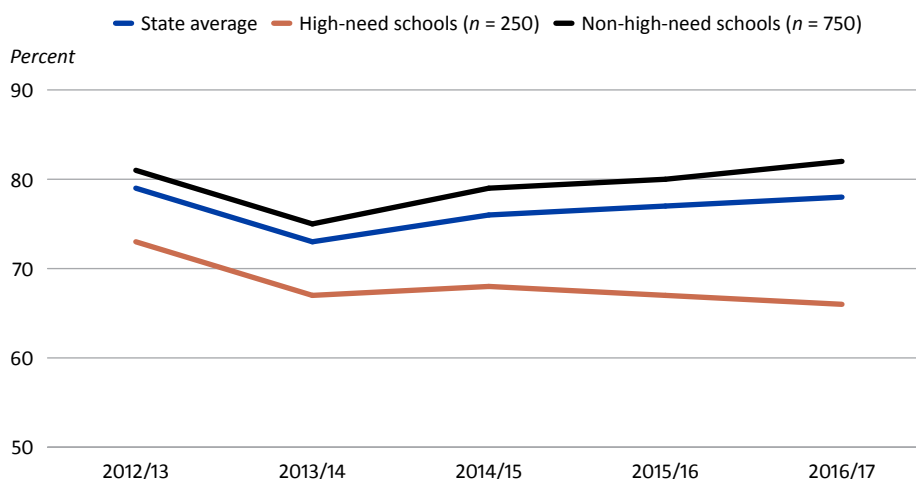Source: Hypothetical data used for illustration purposes.

Creating visual displays of year-to-year trends in mobility and retention

Trend plots, which provide a visual display of rates over time, facilitate the identification of patterns and trends as well as anomalies that require further investigation. Although descriptive statistics can be summarized in tables, trend plots, also referred to as line graphs, are a useful format for visualizing and analyzing patterns in mobility and retention. It is also possible to test the significance of the change in mobility or retention between timepoints using a statistical analysis method designed for repeated measures. Stakeholders might find trend plots useful for forecasting teacher labor force needs. Sometimes trends are analyzed separately for different types of teachers, schools, or districts in order to identify where improvement in retention is needed, which in turn helps stakeholders prioritize the use of limited resources. For example, Lochmiller et al. (2016) examined the annual trend of retention in Kentucky public schools from 2008 to 2012 in order to identify a subgroup that needed attention.

The three-year teacher retention rate in the district in scenario 2 demonstrates the use of a trend plot (figure 2). The trend plot includes the disaggregated retention rates for high-need schools and non-high-need schools. It also includes the retention rates for the entire state for reference. There are several noticeable patterns that the stakeholders and the analyst could discuss. For example, for the past five years the average three-year teacher retention rate in the state remained relatively stable, except for a dip in 2013/14, which the stakeholders note was also a year with a state budget crisis. The teacher retention rate is consistently lower in high-need schools than in non-high-need schools. And non-high-need schools in the district have recovered to their pre-crisis retention rate, as has the state as a whole, but high-need schools in the district have not.

It is important for the analyst to remind stakeholders that visual analysis of trends is just a first step in understanding changes in mobility and retention over time. It is useful for

Figure 2. The three-year teacher retention rate is consistently lower in high-need schools than in non-high-need schools

Source: Hypothetical data used for illustration purposes.

identifying where needs might exist for maintaining retention, but in and of itself it is insufficient for understanding why changes might have occurred.

Comparing mobility and retention rates across districts or states

Stakeholders are often interested in comparing mobility and retention rates across states; however, such comparisons are complicated because rates are not always calculated the same way across states or over time.

Carrying out these comparisons by recalculating the rates so that they are comparable requires access to teacher-level data from each state, which is often not feasible. Recalculating the statistics to make them comparable is also complicated. For example, if one state has a more inclusive definition for stayer than the other, the analyst needs to recalculate the retention rates for one of the states so it aligns with the retention rate for the other. After such an analysis is conducted, it is important for the analyst to communicate the results to the stakeholders of the two states to avoid confusion over the difference between the "official" retention rate and the rate used for the analysis. The issue of compatibility of mobility and retention data can also arise for cross-district comparisons.

Stakeholders in neighboring states might be interested in analyzing teacher interstate mobility, such as how many and which types of teachers are leaving one state to teach in another state or leaving teaching in public schools in the neighboring states. That could supplement information on local supply and demand and help in planning for retention strategies. For example, Podgursky et al. (2016) examined teacher retention, mobility, and attrition between 2005/06 and 2011/12 in Iowa, Minnesota, and Wisconsin. That study produced interstate mobility rates and thereby addressed a common limitation of single-state studies: limited ability to track whether teachers left teaching altogether or moved to teach in another state.

Merging data across states when teachers might be in the data for more than one state requires appropriately matching the teachers in each data file. States do not typically preserve another state's teacher ID, so the same teacher could be in the data file with two different IDs. To match the teachers, the analyst needs to use other uniquely identifying information in combination, such as first and last name, date of birth, or social security number. Once the files are merged appropriately, the analyst will need to identify teachers as stayers, movers, or leavers. This can be done by identifying each teacher's beginning-of-year primary school, meaning the school at which the teacher spends the most time, and then defining teachers who had the same primary school identifiers at the beginning of both years being examined as stayers, teachers who had different primary school identifiers across the years as movers, and teachers who were not in the last year data as leavers (for an example of how to conduct such a comparison, see table 3).

With the data prepared and stayers, movers, and leavers identified, the analyst can calculate teacher retention, mobility, and attrition rates and compare them across states (table 4).

Table 3. Example comparison of mobility across different states, 2015/16–2016/17

Teacher ID	Primary school ID 2015/16	Primary school ID 2016/17	State 2015/16	State 2016/17	Stayer	Mover	Leaver
1	A	A	State 1	State 1	Yes		
2	A	B	State 1	State 2		Yes	
3	B	C	State 2	State 2		Yes	
5	D	—	State 2	—			Yes

— is not available.

Source: Hypothetical data used for illustration purposes.

Table 4. Stayers, movers, and leavers, by state, 2015/16–2016/17

State	Stayers	Movers	Leavers	Total
State 1				
Number	32,000	3,200	4,800	40,000
Percent	80	8	12	100
State 2				
Number	45,000	3,500	1,500	50,000
Percent	90	7	3	100
State 3				
Number	28,000	3,500	3,500	35,000
Percent	80	10	10	100

Source: Hypothetical data used for illustration purposes.

Step 4. Examine relationships using regression models

Step 4 describes the process of examining relationships using regression analysis, which is particularly useful when stakeholders are interested in how multiple teacher, school, or district variables are associated with teacher mobility and retention while other characteristics are held constant. Regression analysis is also useful when stakeholders are interested in whether participation in certain professional development programs is associated with teacher retention and mobility after differences that existed before participation are taken into consideration. For example, in Espel et al. (2019) state education agencies from Colorado, Missouri, and South Dakota asked whether certain teacher, school, or district characteristics were associated with teacher retention.

Examining the relationship between background characteristics and mobility and retention rates

Regression analysis is useful when stakeholders are interested in assessing the relationship between mobility and retention and a focal teacher, school, or district variable, while

holding other teacher, school, or district variables constant. Consider an example where the stakeholders in a state notice that larger districts have lower rates of retention than smaller districts and that many of those who leave larger districts are in the early years of their teaching career.

Although discussions of descriptive findings often conclude that the perceived patterns represent something meaningful, this determination is problematic because other factors, including random events, could produce seemingly meaningful data patterns. For example, the lower retention rate among larger districts might be spurious: the pattern might reflect only a correlation between the size of the district and its locale in the state. In other words, larger districts in the state happen to be predominantly in urban centers with high poverty and low academic achievement. These factors might help explain the turnover.

The point here is that the results of simple descriptive summary statistics often conceal alternative hypotheses that are equally or more plausible. So the analyst and stakeholders need to exercise caution in interpreting the results of simple descriptive analysis and discuss what other factors might be driving the results.

To account for multiple teacher, school, and district characteristics that can influence mobility and retention and to predict mobility and retention rates when investigating a research question, many analysts turn to regression analyses. Regression analysis allows analysts to examine the potential contribution of certain characteristics while statistically holding the potential contributions of other characteristics constant. It also allows analysts to predict mobility and retention, using teacher, school, and district characteristics to better plan for future hiring. Though these types of analyses are not specific to regression, they lend themselves well to this type of investigation. Regression analysis also differs from descriptive statistics in terms of its goal. Specifically, the use of regression is often motivated by the analyst's interest in predicting outcomes.

It is important to know that the type of variable—categorical versus continuous (see table 5 for definitions)—does not dictate whether descriptive statistics or regression should be used. Descriptive statistics can be used to generate cross-tabulations, for describing associations between two or more categorical variables; disaggregated mean tables, for describing associations between two or more categorical variables and a continuous variable; and

Table 5. Definition of key terms for different types of variables

Term	Definition
Categorical variable	A variable with two or more values that have no intrinsic order. For example, the binary variable retention, with two possible values (stayer or leaver).
Continuous variable	A numerical variable. For example, retention rate.
Predictor variable	A variable or set of variables whose influence on an outcome variable is examined in regression analyses. Also referred as independent variable. For example, size of district.
Outcome variable	A variable whose outcome is predicted by a predictor variable or set of predictor variables in regression analyses. Also referred as dependent variable. For example, mobility and retention rates or the binary variable retention, with two possible values (stayer or leaver).

Source: Author's compilation.

Pearson's *r* correlation coefficient, for describing associations between two continuous variables. Likewise, regression analysis can be used to perform linear regressions, for predicting a continuous outcome variable with a set of categorical or continuous predictor variables, and logistic regressions, for predicting a categorical outcome variable with a set of categorical or continuous predictor variables.

An example for the use of regression analysis is to predict district retention rate, which is a continuous outcome variable measured on a scale of 0 to 100. Categorical predictor variables in the analysis could include district locale (urban, suburban, or rural) and district performance category (low or not low), and continuous predictor variables could include total district enrollment, percentage of students in the district who are from racial/ethnic minority groups, and percentage of students in the district who are eligible for the national school lunch program. An example for the use of logistic regression analysis is to predict beginning teachers' two-year school retention, which is a categorical outcome variable (retained or not retained). Categorical predictor variables in the analysis could include the presence or absence of mentoring program at the school (mentoring or no mentoring) and location of undergraduate institution (in-state or out-of-state), and continuous predictor variables could include teacher's age at the time of employment and the percentage of students in the school who are from racial/ethnic minority groups.

Regression has a clear advantage over descriptive analysis when the relationship between more than two variables is being investigated. Although cross-tabulations and disaggregated mean tables can be created in such cases, the number of dimensions could quickly become overwhelming. For example, a researcher who wishes to study the relationship among retention, school locale, and teacher gender could produce a three-dimensional cross-tabulation, resulting in a table with eight cells (2[stayer, leaver] × 2[urban, rural] × 2[male, female]). But interpreting patterns in the table might be challenging. As the number of variables increases, interpreting data patterns becomes nearly impossible—even for the most experienced analysts. On the other hand, an analyst can study the relationship between 5 or even 10 variables using regression analysis because it provides readily interpretable results.

Regression analyses examine the influence of a predictor variable or a set of predictor variables on an outcome variable. The equation form of a regression analysis can be written as:

$$\text{Mobility (or retention) rate} = b_0 + b_1(\text{predictor 1}) + b_2(\text{predictor 2}) + \ldots + \text{error.}$$

In this expression the outcome—mobility or retention rate—is predicted by multiple predictors. As mentioned, a regression model can handle both continuous and categorical predictors. When a categorical predictor consists of more than two values, it needs to be included as a series of binary variables. For example, district locale (urban, suburban, rural) would be included as $b_3(\text{urban}) + b_4(\text{suburban})$. Typically, one of the values is omitted from a series, because that value can be expressed as "No" or "0" in all variables in the series. In this example, the remaining value of "rural" can be expressed as "No" or "0" in both "urban" and "suburban."

For the example mentioned at the beginning of this section, the apparent pattern between the size of the district and retention might be expressed as:

$$\text{Retention rate} = b_0 + b_1(\text{size of district}) + \text{error}.$$

Analyzing the data with this regression model—called simple regression because there is only one predictor variable—might show that the relationship is statistically significant, meaning that is unlikely to be a result of random chance. But a subsequent analysis using the following regression model—called multiple regression because there is more than one predictor variable—might show that the relationship between district size and retention rate disappears once the district locale is taken into consideration. The addition of a second predictor to the initial regression model to jointly predict the outcome is often motivated by the need to estimate the strength of the relationship between the initial predictor and the outcome while the influence of the second predictor on the outcome is taken into consideration. This is commonly referred to as statistical control. In this example the analyst is estimating the strength of the relationship between district size and the district retention rate while controlling for the locale of the district:

$$\text{Retention rate} = b_0 + b_1(\text{size of district}) + b_2(\text{locale}) + \text{error}.$$

Regression analysis can also be used to study the relationship between teacher characteristics and retention while district characteristics that might also affect retention are controlled for (box 6).

In box 6 the outcome *Probability of five-year retention* is a continuous variable.[4] In some cases a regression model with a categorical outcome might be more appropriate to use —for which a logistic regression model would be most appropriate. An analyst who was interested in examining the relationship between type of preparation program and two distinct outcomes, such as teachers who were stayers and teachers who were leavers, would need to use a logistic regression in which *Retention* is a binary variable with two possible values (retained and not retained). While useful, logistic regression findings are more difficult to interpret. Communicating findings based on logistic regression is often challenging for analysts because the results are expressed as the log of odds ratios and lack an intuitive meaning. So many analysts prefer converting the results to odds ratios. However, stakeholders might also find odds ratios hard to understand. One recommendation is to calculate and communicate expected probabilities. For example, the analyst might report that the expected probability of a typical new teacher being retained after three years is 70 percent for urban districts and 75 percent for suburban districts, when district poverty level and academic performance are statistically controlled for. Or the analyst might say that working in an urban district is associated with a 5 percentage point decrease in three-year retention among typical new teachers, when district poverty and academic performance are

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4. The example in box 6 is meant to serve as a simplified model for how to explore retention using regression analysis. These models often require additional complexity. Analysts might decide that logistic regression or hierarchical linear modeling are the best methods to address their research questions given the available data. How to specify the regression model is beyond the scope of this report. Interested readers are advised to refer to statistics textbooks such as Howell (2010) or Raudenbush and Bryk (2002).

Box 6. Analyzing relationships while controlling for characteristics in example scenario 3

After examining the difference in the five-year retention rate between teachers prepared in public institutions and teachers prepared in private institutions, the policymakers in State C notice that teachers trained in private institutions have higher retention rates. But the policymakers are unsure whether the mean difference in the retention rate between the two populations of teachers is meaningful or is the result of other factors.

   The analyst suggests performing a regression analysis using the model:

$$\text{Probability of five-year retention} = b_0 + b_1(\text{Type of preparation}) + \text{error.}$$

The analyst asks the policymakers what other characteristics might also be associated with the type of preparation program and retention. After some discussion, they consider the possibility that teachers who are prepared in private institutions are more likely to take jobs in higher-income districts. Because the policymakers are already aware that higher-income districts have higher retention than lower-income districts, they ask the analyst to check the possibility that this factor is behind the apparent association between the type of preparation program and retention.

   To test this possibility, the analyst performs a regression analysis using the model:

$$\text{Probability of five-year retention} = b_0 + b_1(\text{Type of preparation}) +$$
$$b_2(\text{District percent eligible for the national school lunch program}) + \text{error.}$$

After seeing that the significant difference between the two types of preparation programs disappears when household income is taken into consideration, the analyst and policymakers decide the finding of a private–public difference in retention rate could be better understood as a difference in the type of districts in which beginning teachers seek employment. But the analyst cautions the policymakers that the results of regression analysis alone cannot be used to draw causal conclusions. Specifically, neither type of preparation nor household income level should be considered factors affecting teacher retention in the district. Hearing this, the policymakers ask the analyst if there is a way to know whether the type of preparation affects retention. In response, the analyst invites the policymakers to discuss the viability of conducting studies with rigorous designs that might support causal inference, such as experimental or quasi-experimental studies.

controlled for. Most statistical packages come with the option of calculating expected probabilities. For example, the "margins" command in Stata produces such probabilities.

Examining the relationship between program implementation and mobility and retention rates

Mobility and retention rates are sometimes used as the outcome variable in program evaluation. For example, a state might be interested in evaluating the efficacy of its new teacher mentoring program, whose objectives include improving new teacher retention. If the program is introduced to some districts but not to others, the stakeholders and the analyst could examine its efficacy by comparing retention rates between districts that participate in the program and districts that do not. In addition to randomly assigning districts to the program, one method of examining efficacy is to match participating districts and nonparticipating districts in terms of retention rate before the program and in terms of other characteristics that might be associated with retention (such as district academic performance). This matching would yield two groups of districts with equivalent pre-program retention rates and other characteristics associated with retention and make it unnecessary to hold those factors constant during the regression analysis. However, state teacher mentoring programs are often universal, in that all districts in the state are required to participate. When that is the case, how can the association between program participation and teacher retention be studied?

One approach is to examine the fidelity of program implementation (the degree to which the program was implemented as intended) and its relationship to teacher retention. The variations that exist across districts in terms of fidelity of implementation make it possible to this. But a positive association between fidelity and retention does not permit causal interpretation. Other factors beyond faithful program implementation might be driving the higher retention rates. Still, a positive association could lead stakeholders to hypothesize that the mentoring program is related to higher retention and that the state might want to conduct more rigorous studies to assess the impact of mentoring programs on retention.

The concept of fidelity of implementation, as well as its measurement, is complex and beyond the scope of this report.[5] But consider an example in which the state mentoring program office has monitored the fidelity of implementation in each district and assigned a rating ranging from 1, minimal implementation, to 10, full implementation, to each district. The analyst could obtain district fidelity ratings and use them in the regression analysis. The analyst would start with the following initial regression model:

$$\text{Retention rate} = b_0 + b_1(\text{Fidelity of implementation}) + \text{error}$$

This regression model[6] might show that districts' fidelity in implementing the new teacher mentoring program has a weak and nonsignificant positive relationship with the retention rate of new teachers. In other words, it might be that the better the fidelity with which a

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5. There are several resources for interested readers—for example, Century et al. (2010) and O'Donnell (2008).
6. In practice, constructing regression models involves more than choosing predictor variables. For example, sometimes variables are transformed using logarithms to give a highly skewed variable a more normal (bell-curve shaped) distribution. Other times, an error term is split into two sources, to reflect "nested" structures

district implements the new teacher mentoring program, the higher the new teacher retention rate for the district. At this point the relationship remains suggestive and therefore merits further examination. The analyst might also hear from the program manager that affluent suburban districts often have their own mentoring programs that replace the state mentoring program, resulting in lower fidelity scores among those districts. The analyst then runs separate analyses for affluent suburban districts and the rest of the districts in the state and finds a positive and significant relationship between fidelity and retention in the districts without their own mentoring program and no relationship in the districts with their own mentoring program. The analyst might further refine the regression model by including district characteristics that are likely to be associated with teacher retention, such as academic performance before the introduction of the mentoring program. Regression analysis allows for the examination of the relationship between program implementation and retention, and the same analysis can be repeated separately for districts with different characteristics (box 7).

in the data—such as teachers nested in districts. Statistics textbooks such as Howell (2010) or Raudenbush and Bryk (2002) provide additional details.

Box 7. Analyzing relationships between program implementation and retention in example scenario 1

A primary reason that stakeholders in State A wanted to study retention among beginning teachers is to see whether their new statewide teacher mentoring program is improving retention. Eager to know this, the stakeholders ask the analyst to verify the effect of the program. The analyst explains that because the mentoring program is mandatory to all new teachers in the state, it is not possible to conduct a study that draws a causal conclusion, such as an experimental study. Noting the variation across districts in the fidelity of implementing the program, however, the analyst suggests an analysis of the association between the fidelity of implementation and retention.

The analyst performs a regression analysis using the following model:

$$\text{District retention rate} = b_0 + b_1(\text{Fidelity of implementation}) + \text{error}.$$

This analysis confirms that districts with higher fidelity of implementation have higher retention rates among beginning teachers. As the analyst explains the results, the stakeholders ask if there is any way to know whether the strength of the relationship is similar in low-performing districts with historically lower retention rates and in other districts with higher retention rates. To answer this question, the analyst performs a separate analysis, using the same model described above, for low-performing districts and for the rest of the districts in the state. The results confirm that the fidelity–retention relationship is as strong in low-performing districts as in the rest of the districts.

Although the analyst performed two separate analyses, one for low-performing districts and one for the rest of the districts, an alternative way to address the same question would have been to include the indicator for low-performing district as a covariate as well as an interaction between that variable and fidelity. This method is called moderator analysis. The analyst performed two separate analyses instead, for ease of communication.

A word on "correlation is not causation"

The analyses discussed in this section, including those in the example scenarios, are designed to analyze association but not causation. For example, after conducting the study described in scenario 3, policymakers might conclude that the type of teacher preparation program is associated with where new teachers seek employment, which in turn is associated with teacher retention. These results provide policymakers with preliminary evidence suggesting that the apparent difference in retention between private and public institutions is attributable to a difference in the type of districts in which beginning teachers seek their first employment rather than to a difference in teacher preparation between private and public institutions. Likewise, stakeholders in scenario 1 might conclude that the fidelity of implementation of a mentoring program is associated with teacher retention. But it would be incorrect for those stakeholders to conclude that implementing mentoring programs with higher fidelity causes better teacher retention. Rather, the results will hopefully motivate more rigorous studies to investigate whether mentoring programs indeed cause increased retention, including in low-performing districts.

This issue is summarized by the expression "correlation is not causation," which means that just because two variables are correlated does not necessarily mean that one variable is causing the other. This is important to remember especially when evaluating programs in which mobility or retention is the outcome variable, because stakeholders are often most interested in whether the program has the desired impact on mobility or retention. The question of whether a program works can be assessed only by studies that permit causal interpretations, such as randomized controlled trials, in which participants are randomly assigned to conditions, and quasi-experimental designs, in which statistical adjustments and matching of participants tries to account for differences between participants who take up a program and participants who do not.

A hypothetical randomized controlled trial for scenario 1 might place individual districts in high- versus low-fidelity conditions by randomly withholding state support for program implementation. A hypothetical quasi-experimental design for scenario 3 might match teachers prepared in private institutions with teachers prepared in public institutions based on their background characteristics, creating two groups of teachers that are equivalent in terms of background characteristics.

Because randomized controlled trials and quasi-experimental designs permit comparison of two equivalent groups aside from the focal factor—fidelity of implementation—the difference in retention between the two groups must be caused by the difference in the fidelity of implementation. In contrast, regressions are used to statistically hold constant the differences between the two groups in background characteristics, without actually creating two groups that are equivalent. The U.S. Department of Education's What Works Clearinghouse (2020) considers randomized controlled trials and quasi-experimental designs capable of yielding causal conclusions.

Final remarks

This report—and its companion, report 1—might prove useful to state and district education agency teams interested in analyzing teacher mobility and retention. Using the steps and example scenarios provided in both reports, multidisciplinary teams and data analysts can identify relevant research questions and produce the data to answer them. With this information in hand, stakeholders can inform local policy decisions relating to teacher mobility and retention with the goal of creating a stable and equitable workforce for all students.

As is mentioned many times throughout the report set, this work should not be completed solely by a data analyst. It is important to have a multidisciplinary team that includes policymakers, program managers, data managers, and data analysts. When such a team collaborates to co-develop research questions and interpret the findings, the team can identify more complete and robust solutions and recommendations.

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