



Nowcasting Teacher Turnover

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Policymakers need timely, local information about teacher turnover to make informed decisions, yet turnover data are typically several years out of date and lack the context to assess whether a district's turnover is high or low relative to similar districts. We assemble district-level teacher turnover data from every state from 2003-04 to 2024-25, along with education, labor market, and economic predictors from 2000-01 to 2024-25, and use them to nowcast turnover in the current school year. We then classify each nowcasted turnover to be lower, higher, or similar to peer districts with comparable turnover trends. We can precisely and accurately classify contemporaneous turnover using pre-trends. Fewer than 1% of districts show turnover inconsistent with their classification. The nowcast also yields national estimates, with turnover rising to 14.6% in 2025-26 before declining to 13.2% in 2026-27.

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Introduction

Teacher turnover shapes the quality of public schooling. Turnover lowers student achievement, both for students whose teachers leave and for schools with high turnover (Ronfeldt et al., 2013; Sorensen & Ladd, 2020), and is concentrated in schools serving students living in poverty and students of color, where the resulting churn is most detrimental (Goldhaber, Lavery, et al., 2015; Nguyen et al., 2020; Nguyen & Redding, 2026). Turnover also rose in many states in the years following the onset of the COVID-19 pandemic (Goldhaber & Theobald, 2023). Yet the information available to those who must respond to turnover has not kept pace with the problem.

Education leaders need access to timely and locally specific information on teacher labor markets. District leaders have access to very little information about teacher turnover prior to the start of the year. Some teachers may alert them in advance about a retirement or a new job, but in many cases, education leaders receive this information late. Leaders need to know this information to ensure students have access to qualified teachers. Late teacher hiring negatively influences student achievement (Papay & Kraft, 2016). Lack of information about turnover could lead school leaders in times of acute fiscal stress to unnecessarily lay off or furlough teachers (Kraft & Bleiberg, 2022).

There are few examples of teacher turnover data for the current school year at the district level. Teacher turnover data are typically several years out of date (Bleiberg & Nguyen, 2026a), and data from the Education Department are also years out of date and will likely be delayed further by budget cuts (American Statistical Association, 2026). Data from the Census Bureau represent the best source of contemporaneous data, but are only available at the county level (Goldhaber et al., 2025; Goldhaber & Theobald, 2023; US Census Bureau, 2026). The same constraints characterize teacher shortage data, where compiling state reports cannot make up for the lack of federal infrastructure on the teacher labor market (Nguyen et al., 2024). In the absence of current measures, researchers and journalists have often turned to teachers stated intentions to leave. Intentions are related to turnover but distinct from it, and prior work recommends against using them as a proxy (Nguyen et al., 2025).

The little information that district leaders do have is devoid of critical context. Some turnover is expected, particularly in larger districts, and turnover can even improve overall teacher quality when less effective teachers leave (Goldhaber et al., 2011; Pham, 2022). District leaders likely expect turnover to be higher when the economy is strong, and teachers leave for higher paying jobs in other sectors (Goldhaber & Theobald, 2023; Nagler et al., 2020). However, raw turnover rates provide relatively little information about whether turnover is contextually high or low. More specifically, teacher turnover measures provide little information about whether turnover is high after considering macro-economic conditions or changes to student enrollment. What leaders need is a benchmark, namely whether their turnover is higher or lower than that of districts with comparable turnover histories. To address these challenges, we collect district-level turnover data for over two decades and combine them with education, labor market, and economic predictors to nowcast turnover through the current school year. We then classify each district's nowcasted turnover as lower than, similar to, or higher than that of peer districts. We ask two research questions:

- 1) To what extent can we estimate teacher turnover for the current school year nationally and by school district?
- 2) To what extent can we contextualize district-level teacher turnover relative to districts with similar turnover trends?

In answering these questions, we make three main contributions. First, we present the first nowcast of teacher turnover for the current school year. We demonstrate a strategy using publicly available data that accommodates the uneven coverage of state turnover data, and we validate the resulting estimates against nationally representative federal surveys and out-of-sample forecasts. Second, we forecast peer-relative classifications that describe whether a district's turnover is likely higher or lower than that of districts with similar turnover trends. Third, we make these data publicly available and will update them annually. This resource (Bleiberg & Nguyen, 2026b) will provide policymakers contemporaneous teacher turnover data rather than out-of-date one-time snapshots. To our knowledge, this is the first publicly available source of teacher turnover data for the current school year at the district-level nationwide.

Data

Teacher Turnover Data

To forecast teacher turnover, we collected district-level data for more than two decades. Figure 1, Panel A describes the number of states that make teacher turnover data publicly available in each year from 1999-00 to 2026-27. Very few states made teacher turnover data available from 2002-03 to 2010-11. The availability of teacher turnover data gradually increased from 2011-12 to 2016-17, increasing from 10 to 40 states. From 2016-17 to 2022-23, we observed data from most states. However, after the pandemic, teacher turnover data dropped precipitously, indicating either decreased interest in teacher turnover or data lags where the most recent year data have not been reported. Figure 1, Panel B, describes the proportion of the 13,299 traditional public-school districts, for which we observed turnover data annually. As expected, the availability of district-level turnover data is closely related to the availability of state data. We observed teacher turnover in at least half of all school districts from 2015-16 to 2023-24, and in 2020-21, we observed teacher turnover data in 88.3% of school districts.

We use various sources of state data. Figure 1, Panel C, describes the type of teacher turnover data observed from each state. Appendix Table C1 includes more detailed information on the type of data and source. All data are publicly available except for 8 states where data were obtained through public records requests.¹ 32 states report 1-year turnover. In 11 states we use public records on government employees, which include teachers. Using the included unique employee identifier or name we can calculate 1-year turnover by observing whether a teacher works in the same district in year $t-1$ and in year t . Missouri and Vermont include 3-year turnover rates. In 6 states we estimate turnover using available data. We estimate turnover in 5 of 6 states using the number of hires or teachers with one year of experience following Reichardt and colleagues (2020). For Florida we use information about average years of experience to estimate the number of new teachers in a district. We then normalize the data by demeaning by

¹ Data were obtained through public record requests from Alaska, Indiana, Missouri, Mississippi, Montana Nebraska, New Mexico, Oregon, and Wyoming.

data type (i.e., 1-year turnover).² We validate the state teacher turnover measures by showing they are correlated with federal data collections. In Figure 2, we show the years in which we were able to validate our observed turnover data against the nationally representative turnover data from the Schools and Staffing Survey (SASS) and National Teacher and Principal Survey (NTPS). On average, the difference between the state data and SASS/NTPS is about 1.4 percentage points. The difference in 2011-12 was approximately 3.7 percentage points, but was 1 percentage point or less in the three other years.

Predictors

We forecast teacher turnover using lagged teacher turnover, education system, labor market, and economic characteristics from 2002-03 to 2024-25. Appendix Table B1 describes the predictors, source, and years the data were available. Appendix Table B2 includes descriptive statistics for the predictors. Education system characteristics include total enrollment, teacher full time equivalents, instructional expenditures per pupil, and ESSER expenditures at the district level from 1999-00 to 2023-24 (USED, 2025a, 2025b). Economic characteristics include education industry employment, median household income, and median household value at the district level from 2009-10 to 2023-24 (US Census Bureau, 2025). Labor market characteristics include per capita personal income, total wages, turnover, and Net Negative Job Flow at the county level from 1999-00 to 2024-25 (Bureau of Economic Analysis, 2026; Bureau of Labor Statistics, 2026a, 2026b).

Methods

Nowcasting Teacher Turnover

We “nowcast” teacher turnover by using forecasting techniques to predict teacher turnover from 1999-00 through the current school year (i.e., 2026-27). Our nowcast predicts current district level turnover using one and two year lagged predictors in an Ordinary Least Squares (OLS) framework. Nowcasting is challenging in the context of our study because teacher turnover and many predictors are not observed for the full panel. We observe data for fewer than half of states from 1999-00 to 2013-14 (Figure 1; Appendix Table C1). Additionally, turnover data is usually not available for any states in the most recent years (e.g., 2025-26). Similarly, data for many predictors are not available from 1999-00 to 2009-10, 2025-26, or 2026-27 (Appendix Table B1). Our estimation strategy allows for district level predictions while simultaneously accommodating missing data. All predictors are discretized into indicators for percentiles. This strategy is similar to unsupervised machine learning approaches that are focused on improving the out-of-sample forecast error (Garcia et al., 2012; Shmueli, 2010). Additionally, we add missing data indicators for all predictors (Josse et al., 2024). The binary predictors for percentiles and indicators for miss dating allow us to predict turnover to predict turnover for each district from 1999-00 to 2026-27.

We create weights to improve the precision and validity of our estimates. First, we estimate the inverse of the standard deviation of turnover within school districts. Second, we estimate the mean number of FTE teachers across the panel. The final weight is the average of the inverse variance and the FTE weights. We use the inverse variance to upweight districts with similar

² After normalizing the data, the 2.1 percent of values that are negative or above 100 are set to 0 or 100. The implausible turnover values are caused by the normalization procedure, and our results are robust to not altering the data.

turnover across time and to down weight districts with noisy observed turnover. Using the average FTEs ensures valid national turnover estimates because it upweights large districts, which should not be weighted the same as small districts.

Estimation

We nowcast teacher turnover following the linear equation:

$$Y_{ict} = Y_{it-1} + Y_{it-2} + Y^2_{it-1} + Y^2_{it-2} + \tau_{it-1} + \gamma_{it-2} + \alpha_{ct-1} + \varepsilon_{ct-2} + \mu_{ict1} \quad (1)$$

Where Y equals teacher turnover in district i , county c , and year t . We include one- and two-year lags for all predictors. We include Y_{it-1} and Y_{it-2} , which are one- and two-year lagged turnover and their quadratics. τ_{it-1} and γ_{it-2} are one- and two-year lagged district level education, economics, and labor market predictors. α_{ic-1} and ε_{ic-2} are one and year lagged county level education, economics, and labor market predictors. μ is the standard error clustered by school.³

Peer-relative Classifications

Next, we estimate forecast classifications for each district in 2026-27. We estimate the within district slope of predicted teacher turnover for each district from 1999-00 to 2025-26. Because we use predicted turnover we can create forecast classifications for all districts. Additionally, the predicted district turnover slopes reflect prior observed turnover after controlling for education, economic, and labor characteristics. We then divide districts into 50 groups based on quantiles of predicted district turnover slopes. The districts within each group have similar turnover trends prior to 2026-27. We then create a 2026-27 turnover index, which is normalized to have a minimum value of 0 and a maximum value of 100. Within each of the 50 groups, we classify the bottom quartile as low turnover relative to peers, the middle two quartiles as turnover similar to peers, and the top quartile as high turnover. For example, low turnover implies turnover will be *lower* in 2026-27 than peer districts with similar turnover trends in previous years. The high turnover classification implies turnover will be *higher* in 2026-27 than peer districts with similar turnover trends in previous years.

The classifications are motivated by the limitations of our data and improving the usefulness of the forecast for policy makers. The lack of available data from 2024-25 and 2025-26 limits the precision of district level turnover estimates in 2026-27. However, we can estimate 2026-27 forecast classifications with a high level of precision. In addition, the classifications are arguably more useful for district and state education officials. The classifications provide information about forecasted turnover based on previous trends. The forecast classifications convey critical context about whether turnover is improving or getting worse relative to peers.

Results

Describing Turnover Across Time

The nowcast can be used to describe trends in turnover over time. Figure 3 presents national teacher turnover rates from 2000-01 to 2026-27, with shaded regions indicating recession periods. The confidence intervals are smaller in years where more turnover is observed and larger in years where turnover is not observed, like 2026-27. From 2002-03 to 2016-17, turnover

³ To estimate the standard error of the forecast we multiply the RMSE by an indicator for whether turnover is observed in a specific district and year.

remains stable at around 11% to 13%. Turnover began to slowly increase, moving from 13.2% in 2017-18 to 15.3% by 2023-24. We predict high turnover 2025-26 (i.e., 14.6%), reflecting economic conditions and post-pandemic changes. In 2026-27 we predict that turnover will decline 1.7 percentage points to 13.2%. However, we present this result with caution because of the limited data available in the year prior. Exploring descriptive trends in the predictors we use in the nowcast provides some potential insights into the forecasted changes in teacher turnover. We find that lagged student enrollment declines and turnover for all education staff increases.

Nowcast Robustness Checks

Model Fit

We find that the preferred OLS specification has better model fit than other estimators. Appendix Table A1 describes model fit statistics using alternative estimators. The primary estimation strategy described in equation 1 is OLS with average inverse variance and FTE weights. Appendix Table A1, Panel A, describes Root Mean Squared Error (RMSE), R^2 , and Mean Absolute Error (MAE) for OLS, random effects, and Least Absolute Shrinkage and Selection Operator (LASSO) models. The RMSE is smallest and R^2 is largest for the primary approach. Using weights to account for the variance of turnover improves model fit by down weighting districts with “noisy” turnover that changes substantially from year to year (Bleiberg & Nguyen, 2026a).⁴ Appendix Table A2, Panel B, shows model fit for OLS with average inverse variance and FTE weights, by state data type. RMSE for states that report 1-year turnover rates is smaller than for states that report salary records, 3-year turnover, or where turnover is estimated.

Out of Sample Forecast

The similarity in model fit across out of sample forecasts suggest that reliability of nowcast predictions is strong. Appendix Table A2 describes the out of sample model fit for the nowcast. Following Tashman (2000) we estimate model fit within a rolling window. Appendix Table A2, Panel A includes the results from models where data from 2000-01 through the last year in the window are used to forecast outcomes in the prediction year. Appendix Table A2, Panel B includes the results from models where data from 2000-01 through the last two years in the window are used to forecast outcomes in the prediction year. Across both panels RMSE ranges between 0.0307 and 0.0354. The similarity in RMSE across models suggests that accuracy of the model is not driven by data from a particular year. Additionally, the results from Appendix Table A2, Panel B suggest that RMSE does not substantially increase when predicting turnover using only data from two years prior. This is particularly relevant when evaluating the reliability of nowcast estimates in 2026-27 because in many districts, turnover is not observed in 2024-25 or 2025-26.

Balance on Missing Data

We find that missing turnover data does not substantially bias the nowcast. Appendix Table A3 describes whether districts with missing turnover data have systematically different characteristics at baseline. Appendix Table A3 includes correlations from regressions where baseline predictors are regressed on an indicator for missing turnover and the sample is restricted to include data from the years 2017-18 to 2024-25. We find some small correlations between baseline predictors in 2017-18 and the indicator for whether turnover is missing. Baseline

⁴ The maximum-likelihood random-effects model and LASSO models are not estimable with analytic weights.

turnover in 2017-18 is significantly higher (0.022 SD) in years that turnover is not observed. Overall, the size of the differences is 0.06 SD or smaller for all baseline predictors except education industry turnover. This suggests that the magnitude of bias from missing data is not substantial. Our strategy of modeling missing data and controlling for education, labor market, and economic characteristics should account for the remaining bias from missing turnover data (Josse et al., 2024). Nowcast estimates for districts with high levels of missing data should be interpreted with caution.

Alternative Discretized Predictors

The model fit is robust to alternative numbers of bins for the discretized predictors. In the primary model each of the continuous lagged predictors is discretized into percentiles. Appendix Table A4 describes the model fit when different numbers of bins are used in the nowcast. Using fewer than 99 bins slightly increases the precision of the model. When 10 through 75 bins are included, RMSE and MAE are slightly higher than the main model. Including more than 99 bins does slightly decrease RMSE and MAE. However, the number of districts decreases greatly, which could result in over fitting the model.

Peer-relative Classifications in 2026-27

Using the predictions from the nowcast we can estimate turnover classifications. Figure 4 includes districts with turnover that is low, similar, and high compared to peers. Each panel in Figure 4 describes the distribution of the turnover index, which is created using pre-2026-27 trends in predicted turnover. The vertical line describes the predicted location of a specific district in 2026-27. For example, turnover in Sigourney Community District in Iowa is green for low turnover relative to peers, East Muskingum Local District in Ohio is grey for turnover similar to peer districts, and Trout Lake District in Washington is red for high turnover relative to peers. Predicted turnover for 2026-27 and classification is included for all districts in the Teacher Turnover Nowcast dashboard (Bleiberg & Nguyen, 2026b).

Using data from 2024-25 we show the classifications contain useful information about teacher turnover. Figure 5, Panel A, describes the distribution of observed turnover in 2024-25 by classifications created using predicted turnover from 2000-01 to 2023-24. The distribution of turnover in 2024-25 for districts classified as low relative turnover is centered to the left of the districts classified as having similar and high turnover relative to peers. There are relatively few districts classified as low or high relative turnover whose actual 2024-25 turnover rates would have placed them into a different group. That pattern indicates that the turnover index used to create that classification can be used by education leaders and policy makers to provide information on turnover trends. Figure 5, Panel B, includes box plots that describe the median, 25th percentile, and 75th percentile of turnover in 2024-25 by classifications created using predicted turnover from 2000-01 to 2023-24 that are weighted. In 2024-25 median turnover is 3.4% for low relative turnover districts (IQR=3.1%-7.6%). For high relative turnover districts in 2024-25, median turnover is 16.9% (IQR=14.4%-19.3%). Observed turnover for districts classified as low turnover is 9.6%, 14.3% for districts with turnover that is similar to peers, 18.9% for high turnover districts, and the differences are statistically significant ($p < 0.001$).

Our strategy of using data from prior years rarely misclassifies school district turnover. We find that 2024-25 turnover is in the bottom quartile for only 106 out of 13,299 districts (0.80%)

classified as low turnover using data from prior years. 2024-25 turnover is in the bottom quartile for only 109 out of 13,299 districts (0.82%) classified as high turnover using data from prior years.

Discussion

In this paper, we ask two questions: the extent to which it is possible to estimate teacher turnover for the current school year, nationally and by district, and whether these estimates can be contextualized in ways that support local educational leaders' decision-making. The results suggest we are able to adequately answer both of these questions. Our work presents the first nowcast of teacher turnover for the current school year, and to our knowledge, the first publicly available source of contemporaneous teacher turnover data at the district level nationwide. Drawing on turnover data assembled from every state and more than two decades of education, labor market, and economic predictors, we show turnover in the current year can be estimated with sufficient precision and validity to inform the decisions of local education leaders.

We make several substantive contributions. First, we classify a district's contemporaneous turnover relative to its peers with a high degree of accuracy. We find that observed turnover is rarely inconsistent with the classification generated from their prior trends (1.6%). Then, the nowcast produces national estimates that track recognizable economic and post-pandemic dynamics, with turnover rising to 14.6% in 2025–26 before declining to 13.2% in 2026–27. Next, most consequential for practice, the peer-relative classifications convert a raw turnover rate into the information that leaders most need: whether turnover is high or low given a district's context and history.

The national trajectory produced by the nowcast is consistent with a teacher labor market that responds to broader economic conditions and adds to a growing body of evidence that the teacher labor market did not return to its pre-pandemic equilibrium (Bacher-Hicks et al., 2023; Barnum, 2026; Bleiberg & Kraft, 2023; Camp et al., 2025; Goldhaber & Theobald, 2023). Turnover remained stable at roughly 11% to 13% through the mid-2010s, began to rise around 2016–17, and reached its highest levels in the years following the onset of the pandemic. Prior research indicates teacher turnover moves with the economy and the relative attractiveness of non-teaching employment (Nguyen et al., 2020). We note the projected decline to 13.4% in 2026–27 warrants caution, as turnover is observed for few districts in the two prior years and the estimate consequently carries wider uncertainty. Changes in the predictors, specifically the declining lagged enrollment and rising turnover among all education staff, partially track with the forecasted change (Goldhaber et al., 2026). Taken together, the results suggest the pre-trends in predicted turnover, adjusted for observable conditions, include substantial information about a district's turnover in the current school year.

A central premise of this work is that a raw turnover rate, absent context, tells education leaders little about whether their situation warrants concern and actions. Some turnover is expected, and a portion of it may improve the quality of the teaching workforce as ineffective teachers leave the classroom. A turnover rate of 15% may be routine for one district and alarming for another, and the same rate may reflect a strong regional economy in one year and a district-specific problem in the next. What separates ordinary churn from a genuine staffing problem is whether

turnover is elevated relative to what a district's history and circumstances would predict. The peer-relative classifications operationalize precisely this distinction by benchmarking each district against others with comparable turnover trends, rather than against a single national average that obscures meaningful differences across contexts. The value of such contextualization is reinforced by evidence that turnover is neither randomly nor equitably distributed: it concentrates in higher-poverty, lower-achieving, and higher-minority schools, where the resulting churn is most detrimental to students (Bleiberg & Nguyen, 2026a; Nguyen & Redding, 2026). Situating a district's turnover within its peer group allows leaders to see whether they face a problem their peers have solved or a common challenge that calls for a coordinated response. Overall, the 2024-25 validation indicates that the peer-relative classifications carry real information: the distributions of observed turnover for the low, similar, and high groups are distinct, the differences in group means are statistically significant, and misclassification into the opposite tail is rare.

Our findings speak to a persistent and worsening deficiency in the nation's education data infrastructure. Timely, locally specific information on the teacher labor market is scarce, and the sources that do exist typically describe turnover that is two to three years old and are subject to further delay from budget reductions (Bleiberg & Kraft, 2023). In the absence of contemporaneous measures, researchers and policymakers have often relied on teachers' stated intentions to leave, yet intentions are a weak proxy for actual turnover (Nguyen et al., 2024). The nowcast addresses this gap directly, producing estimates of turnover for the current year and making them publicly available and annually updated (Bleiberg & Nguyen, 2026a). We view this resource as a public good of the same kind as prior efforts to compile and disseminate data on teacher shortages, which have anchored public and policy debate despite the limitations of the underlying data (Nguyen et al., 2025). Replacing out-of-date, one-time snapshots with annually updated data is a critically important contribution.

Implications for Education Data Infrastructure

A substantial contribution of this current work is the effort required to collect national turnover data. Only 32 states report a one-year turnover rate at the district level. In eleven states we constructed turnover from public salary records, in six we estimated it from counts of inexperienced teachers or hires, and in eight we obtained data only through public records requests. The number of states with usable data fell sharply after the pandemic, either because reporting was discontinued or because the lag between the school year and publication grew in length. Federal collections are years out of date and likely to be delayed further, and the most timely federal source, the Quarterly Workforce Indicators, is available only at the county level and not specific to teachers (Bleiberg & Nguyen, 2026a; Bureau of Labor Statistics, 2026b). The nowcast is a response to this environment, but it is a complement to better data rather than a substitute for it. A common definition of one-year district-level turnover, published by every state within a year of the school year's end, would shrink the intervals around every estimate in this paper and would make the peer-relative classifications more precise.

Implications for Policy and Practice

For district leaders, the most immediate application is to reduce the frequency of consequential policy decisions made with little empirical evidence or a high degree of uncertainty. In periods of fiscal instability, policymakers who lack timely information about who is leaving may resort to

layoffs or furloughs that are neither necessary nor equitable, with costs that fall disproportionately on the schools and students least able to absorb them (Goldhaber & Theobald, 2013; Kraft & Bleiberg, 2022). By signaling whether a district's turnover is likely to be higher or lower than that of comparable districts, the peer-relative classifications, along with the forecasted turnover rates, give leaders a benchmark against which to gauge their own staffing outlook before the school year begins and to calibrate recruitment and retention efforts accordingly.

For state education agencies, the nowcast complements the longitudinal data systems that many states maintain and can inform the kind of publicly accessible dashboards we have argued state leaders should build to monitor the teacher pipeline (Nguyen et al., 2024; Nguyen & Redding, 2026). Because turnover concentrates in the schools serving students who can least afford instability, contemporaneous and locally specific data also serve an equity function: they make it possible to identify emerging staffing problems while there is still time to direct resources toward them, rather than several years after the fact. A publicly available, nationwide resource further lowers the barrier for smaller districts and under-resourced states that lack the analytic capacity to generate such estimates on their own.

Limitations and Future Research

Several limitations temper our conclusions. The most important challenge in nowcasting teacher turnover stems from limited state data. The error in the nowcast is a function of imprecision from the lagged predictors, the discretization of those predictors into bins, and the modeling of missing data, and we are unable to decompose the uncertainty attributable to each source individually. A related limitation arises from heterogeneity in how states measure turnover. Although we harmonize across data types, states that make salary records, report three-year turnover, and turnover must be estimated from other records yield less precise estimates than states that report one-year turnover. The classifications, moreover, rely on predicted rather than observed turnover, and estimates for districts missing turnover data in most years should be interpreted with caution. As is common in turnover research using administrative data, we are also not always able to distinguish teachers who leave the profession from those who move between schools or states (Gilmour et al., 2022; Goldhaber, Grout, et al., 2015). We partially address this by harmonizing across types of turnover data. Additionally, we observe high quality one-year turnover and salary records in 84.3% of states (i.e., 43 out of 51) (Gilmour et al., 2022). The evidence from our out-of-sample forecasts and from the balance of baseline characteristics across observed and missing districts nonetheless suggests the nowcast produces valid estimates.

These limitations point to several avenues for future research. Linking administrative records across states would allow the field to distinguish moves from exits and to sharpen the measurement of turnover that our harmonization can only approximate. Extending the nowcast below the district level, to particular subject areas, such as mathematics and special education, or to individual schools, would help address the localized nature of staffing challenges (Goldhaber et al., 2020; Nguyen et al., 2025). Finally, because we commit to updating the resource as new data are released, the accuracy of the nowcast will improve over time, and the accumulating series of annual estimates will itself become a longitudinal record of district-level turnover that can support research beyond the immediate forecasting aims of this study.

Conclusion

Education leaders make consequential staffing decisions each year with remarkably little timely information. This paper demonstrates that publicly available data can be collected and organized to nowcast teacher turnover in the current school year, to situate a district's turnover against that of its peers, and to do so with sufficient accuracy to be useful for practice. By making these estimates public and committing to update them annually, we aim to replace the out-of-date, one-time snapshots that leaders currently rely on with a living resource that reflects current conditions. Timely and locally specific information is a precondition for the targeted and equitable response that the persistent challenge of teacher staffing demands.

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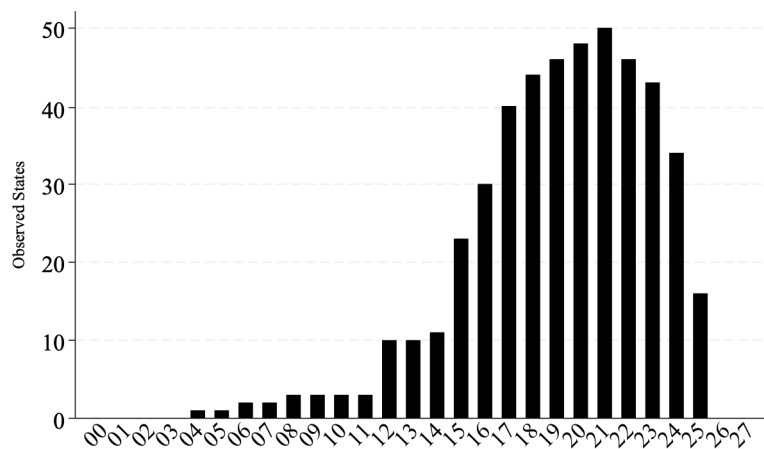
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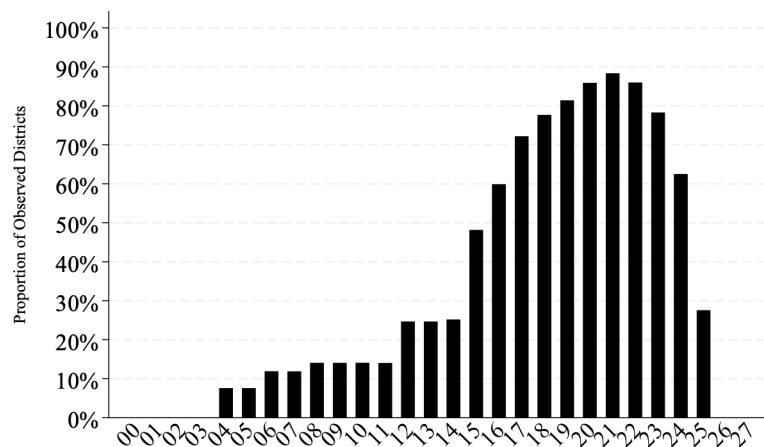
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Figure 1. Teacher Turnover Data Description

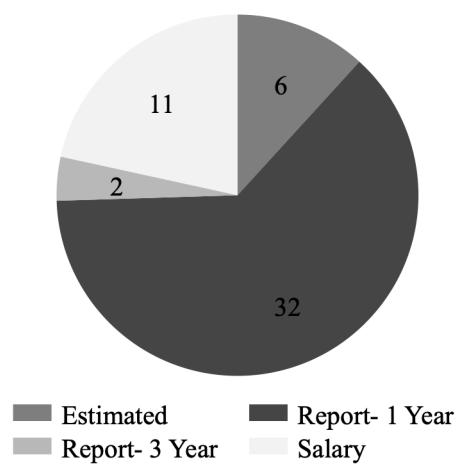
Panel A. Observed States



Panel B. Proportion of Observed Districts

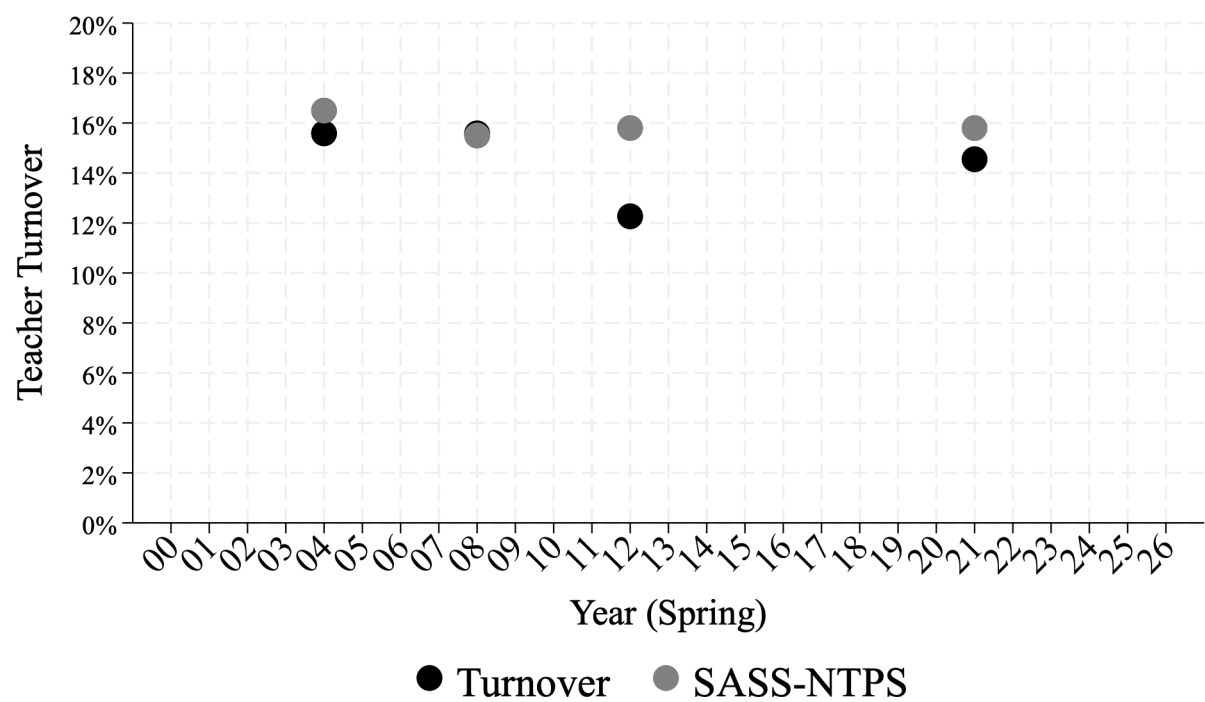


Panel C. State Data Source Types



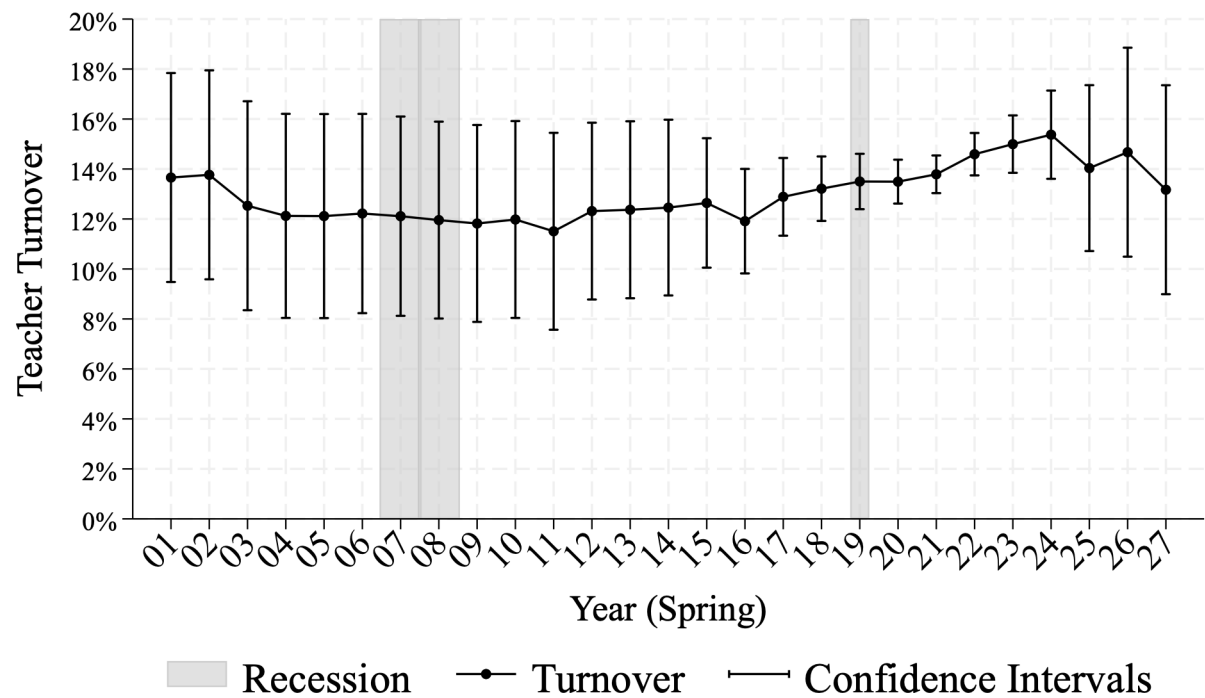
Note: Years in panels A and B are spring-term years (e.g., 2023–24 appears as 2024). See Appendix Table C1 for more details on turnover data types by state.

Figure 2. Turnover Data Validation



Note: Years are spring-term years (e.g., 2023–24 appears as 2024). Turnover describes the average turnover from state data sources. SASS-NTPS is turnover is available from Taie and Lewis (2023).

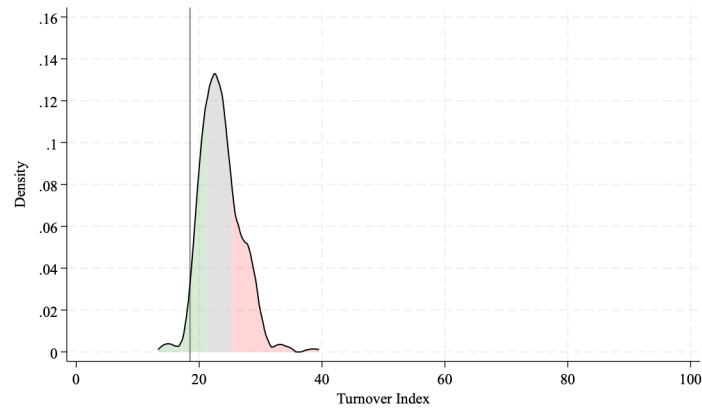
Figure 3. National Teacher Turnover Forecast



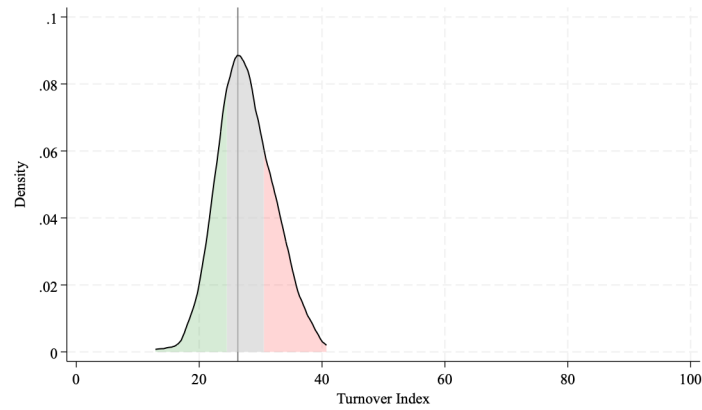
Note: Years are spring-term years (e.g., 2023–24 appears as 2024). The forecast confidence intervals use the standard error from the regression model and adds the RMSE multiplied by the proportion of districts missing data in a specific year.

Figure 4. Forecast Index for Specific Districts

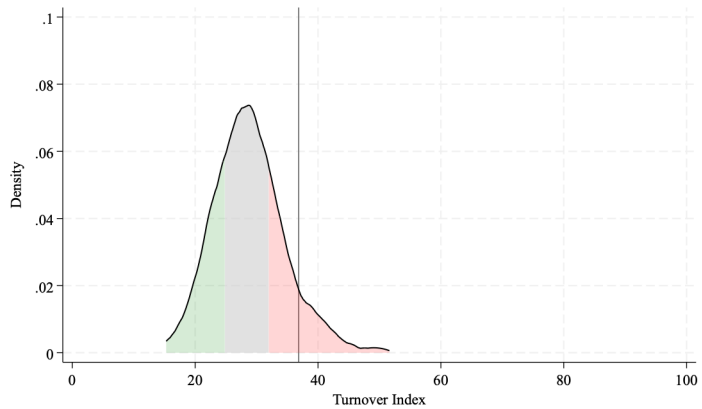
Panel A. Low Turnover Relative to Peers- Sigourney Community School District, Iowa



Panel B. Similar Turnover Relative to Peers- East Muskingum Local District, Ohio



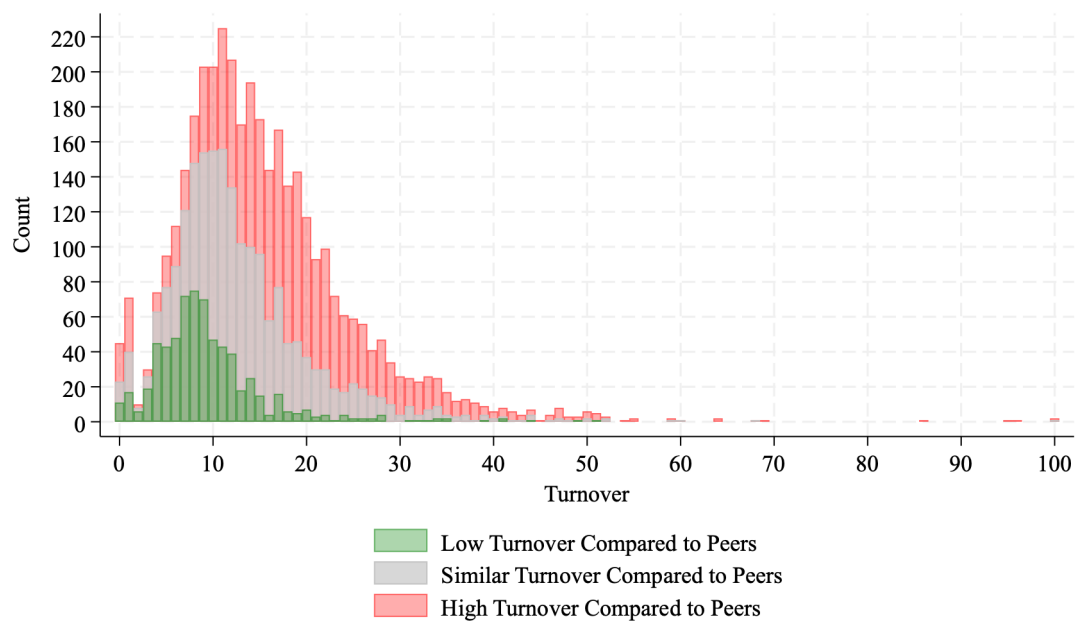
Panel C. High Turnover Relative to Peers- Trout Lake District, Washington



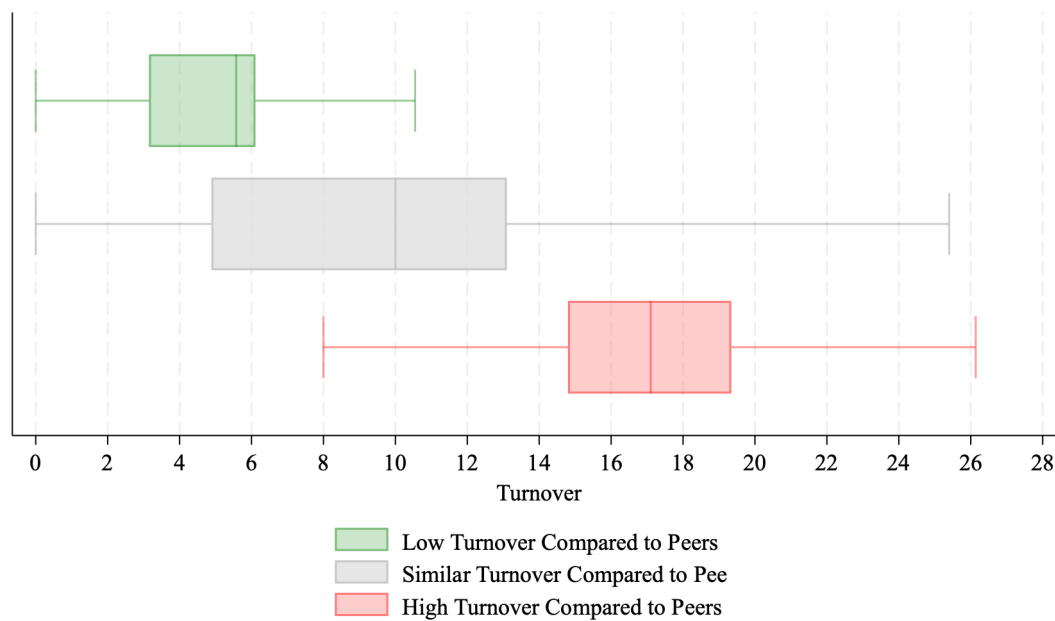
Note: Kernel density plots describe the distribution of the turnover index in 2026-27. The turnover index is estimated within 50 quantiles of predicted turnover from 2000-01 to 2025-26 and normalized to have a range of 0 to 100.

Figure 5. Turnover in 2024-25 by Classification

Panel A. Stacked Histogram of Turnover by Classification



Panel B. Box of Turnover by Classification



Note: Panel A describes the distribution of turnover observed in 2024-25 by classification estimated using data from prior to 2024-25. Box plots in Panel B describe median and IQR of turnover in 2024-25 by classification estimated using data from prior to 2024-25. Estimates in Panel B use weights (i.e., inverse variance and FTE). The differences in turnover by classification in Panel B are statistically significant ($p < 0.001$).

Appendix Table A1. Description of Model Fit

Panel A. Model Fit by Estimator				
Estimator	RMSE	R ²	MAE	N
OLS	0.094	0.353	0.058	124,266
OLS (Inverse Variance Weights)	0.051	0.641	0.057	124,266
OLS (FTE Weights)	0.071	0.512	0.061	124,266
OLS (Avg Inverse Variance & FTE Weights)	0.032	0.797	0.059	124,266
Random Effects	0.088	0.357	0.064	124,266
LASSO Cross Validation	0.096	0.306	0.061	124,266
LASSO Bayesian Information Criterion	0.095	0.320	0.060	124,266
Panel B. Model Fit by Teacher Turnover Data Type				
Data Type	RMSE	R ²	MAE	N
Estimated	0.034	0.795	0.096	8,622
Turnover 1 Year	0.026	0.871	0.052	76,385
Turnover 3 Year	0.031	0.962	0.071	3,101
Salary Records	0.037	0.616	0.063	36,158

Note: Inverse variance weights are equal to one divided by the standard deviation of turnover within school districts. FTE weights are equal to the number of teachers in a district averaged across the panel. RMSE=Root Mean Square Error; MAE=Mean Absolute Error.

Appendix Table A2. Out of Sample Validity

Panel A. Rolling RMSE with Turnover Observed in t-1 and t-2			
Sample	RMSE	Turnover t-1 N	Turnover t-2 N
2001-2017	0.0332	7,961	6,403
2001-2018	0.0336	9,597	7,961
2001-2019	0.0335	10,331	9,597
2001-2020	0.0333	10,822	10,331
2001-2021	0.0328	11,421	10,822
2001-2022	0.0328	11,747	11,421
2001-2023	0.0326	11,431	11,747
2001-2024	0.0326	10,409	11,431
2001-2025	0.0323	8,311	10,409
Panel B. Rolling RMSE with Turnover Observed in t-2			
Sample	RMSE	Turnover t-1 N	Turnover t-2 N
2001-2017	0.0349	NA	6,403
2001-2018	0.0352	NA	7,961
2001-2019	0.0344	NA	9,597
2001-2020	0.0337	NA	10,331
2001-2021	0.0335	NA	10,822
2001-2022	0.0333	NA	11,421
2001-2023	0.0333	NA	11,747
2001-2024	0.0335	NA	11,431
2001-2025	0.0329	NA	10,409

Note: Panel A includes the results from models where data from 2001 through the last year in the window are used to forecast outcomes in the prediction year. Panel B includes the results from models where data from 2001 through the last two years in the window are used to forecast outcomes in the prediction year. Years in the first column are spring-term years (e.g., 2023–24 appears as 2024). RMSE=Root Mean Square Error.

Appendix Table A3. Balance on Missing Turnover Outcome

Baseline Covariate	Level	Mean Difference	P-Value
Turnover (Adjusted)	District	0.022	0.003
Ed Industry Turnover	County	0.102	<0.001
Ed Industry NNJF	County	0.038	<0.001
Total Enrollment	District	-0.051	<0.001
Income (Per Capita)	County	-0.004	0.560
Ed Industry Total Quarterly Wages	County	0.060	<0.001
Teacher FTEs	District	-0.056	<0.001
Ed Industry Employment	District	-0.027	0.001
Median Income	District	-0.044	<0.001
Instructional Expenditures Per Pupil	District	0.027	0.001
Median Household Value	District	-0.026	<0.001

Note: Baseline covariates standardized with a mean of 0 and a standard deviation of 1 in 2018.

Appendix Table A4. Alternative Bin Sizes

Bins	RMSE	R²	MAE	N per Bin
10	0.035	0.747	0.060	1,052
20	0.034	0.766	0.059	526
50	0.033	0.782	0.059	210
75	0.032	0.790	0.059	140
99	<i>0.032</i>	<i>0.797</i>	<i>0.059</i>	<i>105</i>
120	0.032	0.803	0.059	88
200	0.031	0.817	0.059	53
300	0.030	0.831	0.058	35
400	0.029	0.842	0.058	26

Note: N per Bin is the number of school districts observed per year in each bin. In equation 1 predictors are discretized to have 99 bins. RMSE=Root Mean Square Error; MAE=Mean Absolute Error.

Appendix Table B1. Nowcast Predictor Data Sources

Predictor	Level	Source	Years
Teacher Turnover	District	See Appendix Table C1	2004-2025
Education Industry Total Employment	District	ACS	2011-2024
Median Household Income	District	ACS	2011-2024
Median Household Value	District	ACS	2011-2024
Per Capita Personal Income	County	BEA	2001-2024
Total Enrollment	District	CCD	2001-2024
Teacher Full Time Equivalents	District	CCD	2001-2024
Instructional Expenditures Per Pupil	District	CCD	2001-2024
Education Total Wages Quarter 3	County	QCEW	2001-2025
Education Industry Turnover	County	QWI	2001-2025
Education Industry NNJF	County	QWI	2001-2025
ESSER Spending	District	USED	2021-2023

Note: Education Industry is North American Industry Classification System code 6111. Years in the fourth column are spring-term years (e.g., 2023–24 appears as 2024). ACS=American Community Survey; BEA=Bureau of Economic Analysis; CCD= Common Core of Data; ESSER=Elementary and Secondary School Emergency Relief Fund; NNJF=Net Negative Job Flow; QCEW=Quarterly Census of Employment and Wages; QWI=Quarterly Workforce Indicators; USED=United States Department of Education.

Appendix Table B2. Descriptive Statistics for Predictors

Predictor	Mean	SD	Min	Max	N
Teacher Turnover	14.8	11.5	0.0	100.0	104,860
Education Industry Total Employment	1,805.5	11,409.2	0.5	1,169,886.0	146,661
Median Household Income (Ks)	59.7	23.4	6.3	248.1	153,744
Median Household Value (Ks)	135.1	159.0	0.0	1,998.9	153,653
Per Capita Personal Income (Ks)	42.0	16.7	10.3	532.9	261,424
Total Enrollment (Ks)	3.6	14.7	0.0	1,077.4	268,725
Teacher Full Time Equivalents	230.4	899.3	0.1	70,996.4	264,484
Instructional Expenditures Per Pupil (Ks)	7.3	5.1	0.0	775.8	256,933
Education Total Wages Quarter 3 (Ks)	65,233.3	208,725.0	0.0	2,806,903.0	270,239
Education Industry Turnover	25.2	7.8	0.0	100.0	233,828
Education Industry NNJF	1,057.0	2,601.7	0.0	507,82.0	238,576
ESSER Spending (Ks)	68.7	615.2	0.0	696,96.1	29,908

Note: See Appendix Table C1 for years that predictors are observed.

Appendix Table C1. State Turnover Data Sources

State	Data Type	Years	Source
Alabama	Estimated- Inexperienced	2015-2024	(Alabama State Department of Education, 2026)
Alaska	Report- 1 Year	2012-2024	(Riddle, 2025)
Arizona	Report- 1 Year	2019-2025	(Arizona Department of Education, 2026)
Arkansas	Report- 1 Year	2017-2023	(Arkansas Department of Education, 2026)
California	Estimated- Hires	2015-2024	(California Department of Education, 2026)
Colorado	Report- 1 Year	2017-2025	(Colorado Department of Education, 2026)
Connecticut	Report- 1 Year	2012-2024	(Connecticut State Department of Education, 2026)
Delaware	Report- 1 Year	2015-2025	(Delaware Open Data Portal, 2026)
DC	Report- 1 Year	2016-2025	(DC Office of the State Superintendent of Education, 2026)
Florida	Estimated- Avg Experience	2015-2025	(Florida Department of Education, 2026)
Georgia	Report- 1 Year	2015-2023	(Georgia Department of Audits and Accounts, 2026)
Hawaii	Report- 1 Year	2017-2025	(Hawaii State Department of Education, 2026)
Idaho	Report- 1 Year	2020-2023	(Idaho State Department of Education, 2026)
Illinois	Report- 1 Year	2012-2022	(Illinois State Board of Education, 2026)
Indiana	Report- 1 Year	2012-2021	(M. Black, personal communication, Spring 2025)
Iowa	Report- 1 Year	2017-2024	(Iowa Department of Education, 2026)
Kansas	Salary	2015-2024	(Kansas OpenGov, 2026)
Kentucky	Report- 1 Year	2017-2024	(Kentucky Department of Education, 2026)
Louisiana	Report- 1 Year (Regional)	2014-2023	(Louisiana Department of Education, 2026)
Maine	Estimated- Inexperienced	2021-2024	(Maine Department of Education, 2026)
Maryland	Salary	2017-2025	(Maryland State Department of Education, 2026)
Massachusetts	Report- 1 Year	2008-2025	(Massachusetts Department of Elementary and Secondary Education, 2026)
Michigan	Report- 1 Year	2020-2024	(Michigan Department of Education, 2026)
Minnesota	Salary	2015-2025	(Minnesota Professional Educator Licensing and Standards Board, 2026)
Mississippi	Report- 1 Year	2017-2024	(Mississippi Department of Education, personal communication, May 21, 2025)
Missouri	Report- 3 Year	2018-2023	(Vitt, 2025)
Montana	Salary	2015-2023	(Clausen, 2025)
Nebraska	Report- 1 Year	2012-2024	(Klein, 2015)
Nevada	Salary	2016-2021	(Nevada Policy Research Institute, 2026)
New Hampshire	Estimated- Inexperienced	2016-2024	(New Hampshire Department of Education, 2026)
New Jersey	Report- 1 Year	2016-2024	(New Jersey Department of Education, 2026)
New Mexico	Report- 1 Year	2012-2021	(Friedman, 2025)
New York	Report- 1 Year	2016-2024	(New York State Education Department, 2026)
North Carolina	Report- 1 Year	2017-2025	(North Carolina Department of Public Instruction, 2026)

State	Data Type	Years	Source
North Dakota	Salary	2019-2024	(North Dakota Department of Public Instruction, 2026)
Ohio	Salary	2006-2023	(Ohio Department of Administrative Services, 2026)
Oklahoma	Salary	2015-2024	(Oklahoma State Department of Education, 2026)
Oregon	Report- 1 Year	2019-2024	(Oregon Department of Education, personal communication, May 30, 2025)
Pennsylvania	Salary	2015-2025	(Pennsylvania Department of Education, 2026)
Rhode Island	Estimated- Inexperienced	2018-2023	(Rhode Island Department of Education, 2026)
South Carolina	Report- 1 Year	2017-2024	(South Carolina Department of Education, 2026)
South Dakota	Report- 1 Year	2015-2025	(South Dakota Department of Education, 2026)
Tennessee	Report- 1 Year	2018-2025	(Tennessee Department of Education, 2026)
Texas	Report- 1 Year	2004-2025	(Texas Education Agency, 2026)
Utah	Report- 1 Year	2018-2024	(Utah State Board of Education, 2026)
Vermont	Report- 3 Year	2018-2024	(Vermont Agency of Education, 2026)
Virginia	Report- 1 Year	2016-2022	(Virginia Joint Legislative Audit and Review Commission, 2022)
Washington	Salary	2015-2025	(Washington Office of Superintendent of Public Instruction, 2026)
West Virginia	Report- 1 Year	2016-2022	(West Virginia Department of Education, 2026)
Wisconsin	Salary	2017-2025	(Wisconsin Department of Public Instruction, 2026)
Wyoming	Report- 1 Year	2012-2023	(Harada, 2025)

Note: Years in the third column are spring-term years (e.g., 2023–24 appears as 2024).

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