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Are Effective Teachers for Students with Disabilities Effective Teachers for All?

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WORKING PAPER No. 268-0622 • June 2022

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Contents

Acknowledgments

We would like to thank audience members at the Association for Education Finance and Policy Annual Meeting and the Association for Public Policy and Management Fall Meeting. The research reported here was supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305B200009 to Michigan State University, and CALDER, which is funded by a consortium of foundations (for more information about CALDER funders, see www.caldercenter.org/about-calder). The opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education.

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Abstract

The success of many students with disabilities (SWDs) depends on access to high-quality general education teachers. Yet, most measures of teacher value-added measures (VAM) fail to distinguish between a teacher's effectiveness in educating students with and without disabilities. We create two VAM measures: one focusing on teachers' effectiveness in improving outcomes for SWDs, and one for non-SWDs. We find top-performing teachers for non-SWDs often have relatively lower VAMs for SWDs, and that SWDs sort to teachers with lower scores in both VAMs. Overall, SWD-specific VAMs may be more suitable for identifying which teachers have a history of effectiveness with SWDs and could play a role in ensuring that students are being optimally assigned to these teachers.

Research measuring teacher quality has made tremendous strides over the last several years, but much of this work has shared a common assumption—that teachers' effectiveness does not vary across student subgroups. Student growth measures and common evaluation metrics like in-class observations tend to focus on the overall class; an effective teacher is one who generates higher levels of academic growth, on average, and one who uses practices that reflect a single definition of good teaching.[1] But such approaches obscure the reality that teachers may have skills that benefit some groups of students more than others. Indeed, Loeb et al. (2014) and Master et al. (2016) have documented that teachers are differentially effective at improving academic outcomes for English Learners (ELs), and that prior experience and training are both predictive of teachers' success in supporting these students' academic growth. The work on ELs documents that without disaggregating teacher effectiveness below the class-level, we lack key information about whether teachers are sufficiently meeting the needs of critical student subpopulations. Two broad questions emerge from this concern. First, are some teachers effective at supporting some students more than others? Second, if so, do schools assign students to teachers who are best able to meet their needs?

This paper focuses on whether teachers are differentially effective and their assignment to students with disabilities (SWDs). This student population is important for a few key reasons. For one, SWDs make up approximately 13% of the K-12 student population. The majority of SWDs receive most of their instruction in the general education class.[2] Thus, it is important to understand how general educators impact SWDs. Second, SWDs tend to score lower on math and reading achievement assessments than their nondisabled peers (e.g., Chudowsky & Chudowsky, 2009; Schulte et al., 2016) and many experience worse long-term academic outcomes (Stiefel et al., 2021). Understanding if there are teachers who are more effective with SWDs may help school and district leaders pair SWDs with teachers who can best serve them.

Why might we expect teachers to differ in their effectiveness with SWDs? There is ample literature suggesting that specific instructional practices – such as explicit, systematic instruction – are likely to improve academic outcomes for SWDs (e.g., Gersten, Beckmann, et al., 2009; Gersten, Chard, et al., 2009; Jones & Winters, 2022; Stockard et al., 2018; Torgesen et al., 2001). And these practices may benefit SWDs specifically relative to their nondisabled peers (Connor et al., 2011; Connor et al., 2018). Yet many general educators lack the necessary training to use practices known to support SWDs (e.g., Brownell et al., 2010; Cook, 2002; Sindelar et al., 2010). Only seven states require general education teachers to complete coursework for working with SWDs, and only two require clinical experiences working with these students (Galiatsos et al., 2019). Existing studies suggest that general education teachers receive minimal coverage of special education teaching methods in their coursework, and few have any practice opportunities focused on SWDs (Blanton et al., 2011, 2018; Florian, 2012; Galiatsos et al., 2019). Surveys of general education teachers routinely find that many of them feel underprepared to support the diverse educational needs of SWDs (e.g., Kamens et al., 2000; Sadler, 2005). Thus, it is likely the case that many SWDs are assigned to teachers who do not have the requisite expertise for supporting them. And, within a single classroom, teachers may be more or less effective meeting the needs of SWDs or non-SWDs.

To test the relative effectiveness of general education teachers with SWDs, we leverage Los Angeles Unified School District (LAUSD) administrative data from SY 2007-2008 through SY 2017-2018. As the second largest school district in the United States, Los Angeles provides a useful context to study this question as it has diverse teacher and student populations and a large population of SWDs spread across teachers and schools. Using these data, we generate two different sets of value-added measures (VAMs) for each teacher: one focusing on teachers' effectiveness in improving test scores for SWDs (SWD VAMs) and one focusing on non-SWDs (non-SWD VAMs). With these two measures, we also explore whether teachers have a relative advantage in teaching SWDs, defined as being higher in the SWD VAM distribution than in the non-SWD VAM distribution.[3] We use all three measures to explore the following research questions in the Los Angeles context:

1. Is there evidence that a substantial portion of teachers have a relative advantage in teaching SWD vs non-SWDs and vice-versa?
2. Are higher SWD/non-SWD VAMs associated with observable teacher characteristics? If so, do teachers with higher SWD VAMs share the same observable characteristics as teachers with higher non-SWD VAMs?
3. Do SWDs sort into classes taught by a teacher with high SWD VAMs?
4. Are SWDs sorted to teachers with a relative advantage for instructing SWDs?
5. How do retention rates compare for teachers with high versus low SWD VAMs? Are schools more or less likely to retain teachers with relative advantages for instructing SWDs than those with relative disadvantages?

This study contributes to the literature in several ways. First, we provide multiple measures of teacher effectiveness and document whether teachers are differentially effective at instructing students with and without disabilities. The intuitive question of whether teachers are more effective with one student population than with another brings with it several complex analytical challenges. We demonstrate novel approaches for how researchers could conduct similar kinds of analyses moving forward. Second, we expand on previous literature that has sought to link observable teacher characteristics with more effective teachers (e.g., Kane & Staiger, 2008); here, we conduct a similar analysis on observable teacher characteristics and teachers' SWD and non-SWD VAMs. Finally, we explore how student placement and teacher mobility are correlated with teachers' efficacy and relative advantage. Placing SWDs in classrooms with teachers who are the most effective at instructing SWDs can potentially raise the test scores of these students, but only if schools are able to retain these teachers.

Data

Background and Context

We use data from Los Angeles Unified School District (LAUSD), the second-largest school system in the United States. In 2021, LAUSD enrolled over 520,000 students in grades K-12 and employed nearly 24,000 K-12 teachers (LAUSD, 2022). The LAUSD administrative data contain detailed information on student and teacher characteristics, and the sample is highly diverse across student, teacher, school, and community characteristics including socioeconomic status, race/ethnicity, disability status, teacher quality, and achievement.

In LAUSD, approximately 10% of students are identified as having a disability, and 60% of students with mild or moderate disabilities spend most of their day in general education classrooms (Swaak, 2020). School personnel, outside professionals, and an SWD's parents place the student in the most appropriate educational setting based on their individualized needs. However, to the maximum extent appropriate, LAUSD requires that students spend time with non-disabled peers in a general education classroom setting (LAUSD, 2018, p. 11). Under this condition, it may be preferable for principals to pre-identify which teachers have an advantage in teaching SWDs to help make classroom assignments. In the following section, we describe the required data structure for generating SWD and non-SWD VAMs.

Sample and Data Requirements for Generating SWD and non-SWD VAMs

This study uses student- and teacher-level administrative data spanning from the academic years 2007-2008 through 2017–2018, provided by LAUSD's Office of Data and Accountability and the Division of Human Resources. The data are at the student-year level and include demographic information such as disability status (detailed below), race/ethnicity, gender, free or reduced-price lunch (FRL) eligibility, and English Learner (EL) status, as well as math and English language arts (ELA) state test scores. We normalize each subject's test scores to have a mean of zero and standard deviation of one for each grade-year combination. We include both math and ELA scores because of evidence that SWDs may have different challenges in each subject (e.g., Child et al., 2019; Fuchs et al., 2016). In LAUSD, test score data are collected for students in grades 3 through 8, which limits our sample to these grades.[4] Additionally, while studying teacher quality for SWDs in all classrooms would be ideal, test scores (and correspondingly, VAM calculations) are only available for math and ELA courses.

In this study, we are interested in analyzing the differences in exposure to teacher quality for SWDs and non-SWDs. To compare teachers' non-SWD VAMs relative to their SWD VAMs, our analytic dataset is limited to students attending mainstream[5] classrooms. To ensure teachers have enough observations for both student groups, we further limit the analytical sample of teachers to those with at least 10 non-SWDs and 10 SWDs, totaling at least 20 student observations, between SY 2007-08 and 2017-18.[6] This restriction limits the teacher sample to general education teachers with substantial experience in instructing SWDs. It is important to note that our analysis eliminates general education teachers who do not teach enough SWDs over the period of this study. Given the test score data and teacher restrictions, we observe 578 unique schools, 7,207 unique teachers, and 661,789 unique students with 10.7% of students having ever been classified as SWDs.

Table 1 illustrates the demographic and standardized test information for all students and teachers in our analytical sample. In the first row of Panel A, each student is represented only once. Since many student characteristics change over time (e.g., disability status, free or reduced-priced lunch status, English Learner status), the interpretation of student characteristics for this row is the percent of students who have ever been classified for the specific characteristic. For example, 10.7% of the students within our sample were ever classified as SWDs during the sample period. The test score columns are first averaged within each student across years, then averaged again across students.[7] The LAUSD data include information on 13 disability subcategories. We conduct analyses for SWDs overall and then, for illustrative purposes, focus on the three disability subcategories with the largest percentages of students; we subsume the remaining disability types into an "other" category.[8] The disability categories in our study include *Autism*, *SLD* (specific learning disability), *LSI* (language & speech impairment), and *Other Dis.* (other disability).[9] These categories are not mutually exclusive, which explains why the sum of these columns is greater than the *SWD* column. Almost 85% of students have ever been eligible for free or reduced-priced lunch (*FRL*), 26.6% have ever been classified as an English Learner (*EL*), 73.8% of students are Latino/a, and only 10.3% of students are White.

The remaining rows for student characteristics in Table 1 are listed at the student-year level (i.e., the level of our analysis), and show how student characteristics vary by the different disability types. The second and third rows separate the overall student body between non-SWDs and SWDs. This separation highlights some interesting differences between the two groups of students and provides additional avenues where teachers may differ in effectiveness. Aside from the substantial difference in standardized test scores, SWDs are far more likely to be ELs and male. Of student-years classified as a SWD, 8.1% are classified under *Autism*, 67.9% under *SLD*, 9.4% under *LSI*, and 20.2% under *Other Dis*.

Table 1 Panel B describes the characteristics of teachers within our sample at the teacher-year level. 1.5% of observations hold a special education teaching credential, and 36.4% have a master's or PhD degree. Most teachers within our sample are relatively experienced, with only 2.2% representing teachers within their first two years of teaching (*Novice)*, 6.3% with three to five years of experience (*Early Career)*, 15.0% within six to nine years (*Middle Career)*, and 76.6% with ten or more years of experience (*Late Career)*. Note that since we are restricting the sample to teachers who have had at least ten SWD and ten non-SWDs in their career, this threshold skews our sample towards more experienced teachers than the LAUSD average.

We compare teacher characteristics from our analytic sample to the excluded sample in Table 2. Also, in Table 2, we explore changes to our 10 SWD and 10 non-SWD thresholds by examining how the teacher sample differs when we change the threshold to 6 or 15 students for each subgroup. Compared to the excluded sample, the share of teachers that hold a special education credential decreases substantially once we set the threshold at 6 or above. This is logical since teachers with special education credentials are likely to teach few non-SWDs, whom we need for estimating the non-SWD VAMs. Also, the share of novice and early-career teachers decrease when comparing the excluded sample to our analytic sample. This is likely due to teachers with more experience having more students, both SWDs and non-SWDs, across the 11 years of the dataset. As a robustness check, we also provide the results at each threshold level for *Research Question 1* in online Appendix Figure A1 and for *Research Question 3* in Table

A1. Due to the similarity in results across thresholds, we focus on the 10-threshold sample for the remainder of this paper.

SWD and Non-SWD VAM Calculations

For each subject with available test score data (math and ELA) and year, we create two separate VAMs for each teacher to measure their contribution to student achievement growth, as measured by test scores, for SWDs and for non-SWDs. We estimate the following model separately by students' SWD status:

$$(1) \qquad Ach_{ijt}^{subject} = \beta_1 Ach_{ijt-1}^{math} + \beta_2 Ach_{ijt-1}^{ela} + \boldsymbol{X}_{ijt}\boldsymbol{\Gamma} + \boldsymbol{T}_{jt}\boldsymbol{\Omega} + \theta_t + \varepsilon_{ijt},$$

where *Ach* is either math or ELA achievement, standardized within subject and year, for student i with teacher j in year t. We use a *leave-year-out* method following Chetty et al. (2014), which eliminates the concern of measurement error of previous years impacting the VAM estimate for year t.[10] Also, we control for students' achievement in the prior year in both math and ELA, as the inclusion of the second subject helps to mitigate bias due to sorting and to attenuate measurement error (Lockwood & McCaffrey, 2014). $\boldsymbol{X}$ is a vector of student demographic characteristics and is used to control for potential unobservable factors that may influence a student's test score outside of a teacher's control, which includes indicators of student race, gender, FRL eligibility, EL status, and grade level. Teachers' VAMs are estimated by the coefficients on a set of teacher fixed effects ($\boldsymbol{T}$) and are normalized at the teacher-year level. Normalization allows us to interpret VAMs as the number of standard deviations from the mean teacher in terms of VAM score. θ_t are year fixed effects, and ε is a normally distributed error term. We estimate heteroskedasticity-robust standard errors. This specification was chosen based on a detailed review of the current best practices in VAM modeling, summarized in (Koedel et al., 2015).

Research Question 1. Is there evidence that a substantial portion of teachers have a relative advantage in teaching SWD vs non-SWDs and vice-versa?

Methods

We begin by exploring differences in teachers' relative ranks in SWD and non-SWD VAMs across LAUSD teachers and years. Our analysis focuses on rank ordering because the SWD and non-SWD VAMs are measured from different student populations making them ordinally but not cardinally comparable. That is, since VAMs are measured relative to the mean growth in each group, a SWD VAM of say, 2.3 does not reflect the same learning growth as a non-SWD VAM of the same value. Hence, we cannot say whether a teacher increases achievement in SWDs by a higher or lower amount than she increases achievement in non-SWDs. Instead, we can only say whether a teacher is higher or lower in the distribution of SWD performance amongst her peers relative to her position in the distribution of non-SWD performance.

For each VAM (i.e., math SWD, math non-SWD, ELA SWD, and ELA non-SWD), we define the relative rank to be the percentile the teacher falls into within the VAM distribution for a given year. Once these values are assigned to each teacher, we compute the difference between the non-SWD and SWD VAM percentiles for each subject and year. We label this statistic as the *difference in VAMs* (DVAM), which is defined as:

$$DVAM_{jt}^{subject} = Ptile_{jt}\left(VAM_{Non-SWD}^{subject}\right) - Ptile_{jt}\left(VAM_{SWD}^{subject}\right), \quad (2)$$

where $Ptile(.)$ converts its argument into a percentile. Using Equation (2), we define a teacher as having a *relative advantage in instructing SWDs* when their DVAM is negative. In other words, a teacher who falls in a higher percentile in the SWD VAM distribution than in the non-SWD VAM distribution is defined as having a relative advantage in instructing SWDs. As an example, a teacher in the 80th percentile for SWD VAM and the 50th percentile for non-SWD VAM would have a DVAM of -30 (i.e., 30 percentile points higher in the SWD VAM distribution than the non-SWD VAM distribution).

One concern regarding teacher DVAMs is that VAM estimates can be quite noisy, and so some of the within-teacher variation we see between the two types of VAMs is likely due to random error. To understand the potential extent of this error, we construct a new set of VAMs based on randomly generated groups of SWDs and non-SWDs. Specifically, we randomly assign SWD status to each student (while preserving the total size of and share of SWDs in a teacher's class) and calculate two separate VAMs by group (i.e., SWD or non-SWD) for each teacher using the same method as described above. Since disability status in this case is randomly assigned, any differences in a teacher's "random" SWD and non-SWD VAMs would be due to random noise. We repeat this process 100 times and, following Equation (2), we generate a randomized DVAM for math and another for ELA for each randomization. Finally, separating by subject, we pool each randomized DVAM to generate the random DVAM distribution. This exercise provides us with a baseline distribution to assess how much the original DVAM distribution differs from random estimation error.

In theory, randomizing SWD status should generate SWD and non-SWD VAMs that are similar to each other because each VAM would mainly reflect random error. If the differences in the two original VAMs contain information beyond noise (i.e., if some teachers are better at teaching SWDs than others), the variation in the randomized DVAM distribution should be smaller than the original DVAM distribution. This finding would provide evidence that some teachers indeed exhibit a relative advantage for different groups of students that extends beyond random variation. In the context of this paper, this would indicate that there exist individual teachers who are "better" at instructing SWDs compared to non-SWDs.

Results

Figure 1 provides a scatter plot of each teacher observation by the SWD and non-SWD VAM percentiles. If all teachers were exactly within the same percentile for both student groups (e.g., had the same value-added for each group and no estimation error), the scatter plot would produce a 45-degree line. However, while there is a positive relationship between the percentile of VAMs as seen by the fitted lines, this figure shows that teachers ranked highly in one VAM do not necessarily rank highly in the other. This figure illustrates that some teachers have a relative advantage for one group (i.e., SWD or non-SWD) over another. Table 3 further describes the distribution of VAMs across each group by quintile and subject. One finding is that teachers with the highest (or lowest) VAM for one student group tend to also have the highest (or lowest) VAM for the other student group. For example, Panel A of Table 3 shows that the plurality (9.8%) of math teachers fall into the top quintile (i.e., quintile 5) for SWD VAMs and the top quintile for non-SWD VAMs, with the next largest group (9.0%) of teachers falling into the bottom quintile (i.e., quintile 1) for both VAMs. This pattern persists for ELA teachers, though to a lesser extent. However, for teachers within the middle quintiles, a large majority fall into a bin off the diagonal (i.e., the values in bold) across both subjects. This indicates that teachers closer to the mean for one VAM are more likely to exhibit a relative advantage for SWDs than teachers who fall on the extreme ends of the VAM distribution.

In Figure 2 we illustrate the relationship between teachers' SWD and non-SWD VAMs for math and ELA courses by plotting the difference between the two VAMs (DVAM). The values further to the left of zero on the x-axis indicate a greater magnitude of a teacher's relative advantage towards SWDs. As previously explained, teachers with a relative advantage for SWDs have a negative DVAM, which indicates that the teacher falls into a higher percentile on the SWD VAM distribution than for the non-SWD VAM.

To determine the extent to which the original DVAMs are driven by measurement error, we also compare them to a randomized DVAM, represented by the dotted densities in Figure 2. For both subjects, the variation in the original DVAM is greater than the randomized DVAM, which indicates the relative advantage measures for teachers are larger than what we would expect by chance. We compare the variances of the original and random DVAMs to test the differences of the two distributions. The ratios in the variances are 1.70 for math and 1.47 for ELA. In other words, the variance in the original DVAM distribution for math (ELA) courses is 70% (47%) greater than the variance for the random DVAM distribution for the same subject. These results suggest that the separate SWD and non-SWD VAMs include useful information beyond measurement error and that teachers vary in effectiveness with these two groups of students.

Research Question 2: Are higher SWD/non-SWD VAMs associated with observable teacher characteristics? If so, do teachers with higher SWD VAMs share the same observable characteristics as teachers with higher non-SWD VAMs?

Methods

The current literature suggests that most observable teacher characteristics (e.g., Master's degree, certification status) do not accurately predict teacher effectiveness as measured by VAM scores (e.g., Chingos & Peterson, 2011; Kane & Staiger, 2008). However, it may be that observable characteristics are relatively uncorrelated with teacher VAM scores because current VAMs are calculated across all students, rather than by student subgroups. We explore the possibility that observable characteristics of teachers can help identify those who are better at teaching SWDs (or non-SWDs). To do so, we use a standard linear regression model to estimate if observable teacher characteristics are associated with higher/lower VAMs for each subject (math, ELA) and student group (SWD, non-SWD). Our model is as follows:

$$VAM_{jt}^{subject,group} = \beta_0 + \boldsymbol{X}_{jt}\boldsymbol{B}_x + \boldsymbol{Z}_{jt}\boldsymbol{B}_z + \theta_s + \theta_t + \epsilon_{jt}\ , \tag{3}$$

where VAM_{jt} is a standardized score calculated using Equation (1) for each subject and group. $\boldsymbol{X}_{jt}$ is a vector of teacher characteristics, which includes special education credential, Master's degree or PhD, years of experience, gender, and race. $\boldsymbol{Z}_{jt}$ is a vector of classroom characteristics and controls for the share of non-White/non-Asian, English Learner, free or reduced-price lunch eligible, and SWDs within each classroom. We also control for school (θ_s) and year (θ_t) fixed effects to account for any potential differences across schools and yearly shocks, respectively. We estimate a separate regression for each group's VAM to find the association between VAMs and teacher characteristics. Though the results from Equation (3) are purely descriptive, they can provide valuable insight in determining if higher SWD VAM teachers can be distinguished from higher non-SWD VAM teachers through traditional observable characteristics.

Results

In general, similar to the existing literature for overall VAMs, we do not find strong discernable relationships between teachers' characteristics and SWD or non-SWD VAMs. Table 4 shows the regression results for Equation (3) with each column displaying the coefficients for teacher characteristics across each subject-group combination of VAM. While the special education credential status, education, and experience of teachers are largely uncorrelated with VAMs, there are some differences by teacher gender and race. Across both subjects, female teachers are associated with higher non-SWD VAMs, while there does not seem to be any relationship with SWD VAMs. For teacher race, relative to white teachers, on average, Asian and Latino/a teachers are associated with higher math VAMs for both student groups, while Black teachers are associated with lower math VAMs. These differences in VAMs between teachers of color and their White counterparts are larger for non-SWD VAMs than for SWD VAMs. For example, while Asian teachers exhibit higher math SWD VAMs than White teachers (by 0.140 SD), Asian teachers are expected to have even higher math non-SWD VAMs (by 0.170 SD). The differences across VAM types are statistically significant for Asian and Black teachers, but they are not for Latino/a teachers.[11]

In general, we do not find any statistical differences for ELA VAMs by teacher race. The one exception is that, on average, Black teachers exhibit lower non-SWD ELA VAMs than White teachers. While it is not clear why these relationships emerge, one potential explanation is that, given LAUSD's large Latino/a population (as seen in Table 1, Latino/a students represent 73.8% of the sample), a student-teacher race match effect could be influencing the VAMs (e.g., Dee, 2004; Egalite et al., 2015; Joshi et al., 2018; Wood & Lai, 2022). While this is an intriguing hypothesis, a deeper analysis of this finding is beyond the scope of this study and so we leave it for future research.

Research Question 3: Do SWDs sort into classes taught by a teacher with high SWD VAMs?

Methods

To investigate whether SWDs sort into classrooms taught by teachers with high (or low) SWD VAMs, for all students, we regress their teacher's VAM on SWD status using the following equation:

$$Y_{it}^{subject,group} = \alpha_0 + \alpha_1 SWD_{it} + \theta_{sgt} + \epsilon_{it}, \tag{4}$$

Where $Y^{subject,group}$ represents a teacher's VAM for a given subject (math, ELA) and group of students (SWD, non-SWD) for a given year t. In this equation, SWD indicates if student i is a SWD in year t. θ_{sgt} is a school-grade-year fixed effect and allows us to focus specifically on how SWDs and non-SWDs are being sorted within individual school-grade-year combinations, since this is the level at which student assignment to teachers occurs. The coefficient of interest, α_1 , is interpreted as the expected difference in teacher VAM for SWDs compared to non-SWDs. We conduct two additional analyses. First, we check for heterogeneity in sorting across disability types by replacing the SWD indicator variable in Equation (4) with indicators for a specific disability type (e.g., autism, specific learning disability, speech or language impairment, or other disability).

$$(5) \qquad Y_{it}^{subject,group} = \alpha_0 + \alpha_1\, SWD_{it}X_{it} \; + \; \alpha_2\, SWD_{it} + \alpha_3 X_{it} \; + \theta_{sgt} + \epsilon_{ist}$$

Additionally, in Equation (5), we interact the SWD indicator with different student characteristics to further explore potential heterogeneity by FRL eligibility, EL status, or non-White/Asian status. X represents these student characteristics.

Results

Table 5 provides results from Equation (4) where we estimate the expected difference in teacher VAMs for SWDs compared to non-SWDs. For both subjects, we show the results for SWD VAMs and non-SWD VAMs. We find that SWDs are consistently assigned to teachers with lower VAMs. Note that these are teacher-level VAMs and so they imply that a SWD is placed with a teacher who ranks 0.036 and 0.043 standard deviations (SD) lower in the teacher distribution of SWD and non-SWD value-added, respectively. The analogous estimates for ELA VAMs are .040 and .056 SD, reflecting a similar pattern where SWDs sort into classrooms taught by teachers with lower value-added. All estimates are statistically significant at the 0.1% level.[12]

We conduct a similar analysis to Table 5 but further disaggregate by type (autism, SLD, LSI, and other disabilities) in online Appendix Table A2. For both subjects, each column represents a separate regression where SWD VAM and non-SWD VAM are outcomes. For students with SLD and other disabilities, a pattern similar to Table 5 holds: on average, these students are assigned to teachers with lower VAMs than their non-SWD peers. Relative to coefficients for all SWDs, the coefficients are slightly larger in magnitude for SLD students and slightly smaller for students with other disabilities. On the other hand, students with autism or LSI exhibit little difference in teacher value-added relative to their non-SWD peers.

Table 6 provides results from Equation (5), which furthers the analysis above by examining heterogeneity across different student characteristics. We analyze FRL eligibility in Panel A, EL status in Panel B, and non-White/non-Asian status in Panel C. Across all panels, we find that SWDs that are eligible for FRL, are ELs, or are non-White/non-Asian are assigned to teachers with lower VAMs than non-SWDs without these characteristics (i.e., non-FRL, non-EL, White or Asian non-SWDs). For instance, on average, a non-White/non-Asian SWD has a math teacher with a SWD VAM that is .087 SD lower than a White or Asian non-SWD. Moreover, our estimates suggest that SWDs that are also either (1) FRL-eligible or (2) non-White/non-Asian have teachers with lower VAMs than students that have just one of these characteristics (e.g., non-FRL SWDs, or non-White/non-Asian non-SWDs). This finding suggests that for some groups of SWDs, there may be a compounding pattern of disadvantage, although this effect is relatively small.

Research Question 4: Are SWDs sorted to teachers with a relative advantage for instructing SWDs?

Methods

The previous research question examines whether SWDs sort into classrooms taught by teachers with higher SWD VAMs. Our fourth research question focuses on the DVAM measure to understand how SWDs sort across teachers by teacher relative advantage. In other words, we ask whether SWDs sort towards teachers with higher SWD VAMs relative to their non-SWD VAMs, even if a teacher has low VAMs for both student groups. To answer this question, we indicate a teacher as having a relative advantage for SWDs using the DVAM measure described in *Research Question 1* as the outcome to Equation (4). If a teacher's DVAM is <0, they have a relative advantage in teaching SWDs; otherwise, they do not. As a robustness check to our definition of relative advantage, we also create two additional measures where teachers must have more than a 10 or 20 percentile advantage in teaching SWDs (i.e., a DVAM of <-10 and <-20) to be defined as having a relative advantage. In these two additional definitions of relative advantage, a teacher with a DVAM of -5 would not be said to have a relative advantage for SWDs. However, a teacher with a DVAM of -25 would be defined as having a relative advantage for SWDs. As in *Research Question 3*, we repeat the analysis using indicators for each disability type.

Results

Panel A of Table 7 provides estimates from Equation (4) where the outcome is an indicator variable for relative advantage in teaching SWDs. For math courses, we do not find evidence that SWDs are more likely to be placed with teachers who have a relative advantage in teaching SWDs compared to non-SWDs. However, the results are stronger for ELA; using any of our three definitions of relative advantage, SWDs are 0.6-0.8 percentage points more likely to be assigned to teachers with a relative advantage in teaching SWDs than non-SWDs. When viewed in the context of our results from Table 4, we find that on average, while SWDs have teachers with lower VAMs, SWDs are more likely to be placed with ELA teachers who are comparatively more effective in teaching SWDs.

We perform an analysis similar to that in Panel A of Table 7 that focuses on differences across SWD disability type, shown in online Appendix Table A3. For ELA, the results are relatively similar to those in Table 7 for students with SLD and other disabilities. The results are not statistically significant for students with autism or LSI. For math, while we find a positive effect for students with SLD and other disabilities using our least restrictive definition of relative advantage, this impact is statistically insignificant when using our most strict definition. In general, we do not find statistically significant results for students with autism or LSI.

The relative advantage measure in Panel A of Table 7 is defined *across* school-grades for the entire district. In Panel B, the outcome is a dummy variable which indicates teachers whose DVAMs are strictly less than (i.e., have more relative advantage for instructing SWDs) the median DVAM of all teachers *within* a given school-grade-year combination. In this approach, we assess the relationship between SWDs and the relative advantage measure while only considering teachers with which the student could feasibly share a classroom. Looking within schools strengthens our previous findings. Across both subjects, SWDs are more likely than non-SWDs (by 0.7 and 1.0 percentage points for math and ELA, respectively) to sort into classrooms taught by teachers whose relative advantage is more geared towards SWDs than the other teachers in the school-grade. These results suggest that from a school's perspective, there may be room for efficiency gains from assigning SWDs to teachers who are comparatively stronger at teaching SWDs. We note, however, that from a student or parent's perspective, any notion of efficiency may be outweighed by overall teacher efficacy, since SWDs still receive lower VAM teachers on average.

Research Question 5: How do retention rates compare for teachers with high versus low SWD VAMs? Are schools more or less likely to retain teachers with relative advantages for instructing SWDs than those with relative disadvantages?

Methods

Whether or not a student is assigned to a highly effective teacher (as measured by a teacher's VAM score for each subject and student group) is, to some extent, determined by whether a school is able to retain such teachers. We leverage indicator variables for whether a teacher leaves LAUSD or switches schools within the district.[13] Using Equation (6), we measure how an increase in SWD and non-SWD VAMs relate to a teacher's probability of leaving the district or switching schools. Specifically, we use the following model to understand the association between teacher mobility and each group-VAM for both subjects:

(6) $$Y_{\mathrm{jt}} = \alpha_0 + \alpha_1 VAM_{jt}^{subject,SWD} + \alpha_2 VAM_{jt}^{subject,non-SWD} + \boldsymbol{X}_{jt}\boldsymbol{B}_x + \boldsymbol{Z}_{jt}\boldsymbol{B}_z + \theta_s + \theta_t + \epsilon_{jt}$$

where Y_{jt} indicates one of the two outcomes (i.e., leave LAUSD or switch schools). The remaining components are defined as in previous models.

Additionally, we use the following model to analyze whether teachers with a relative advantage in teaching SWDs are more or less likely to leave LAUSD or switch schools than other teachers:

(7) $$Y_{jt} = \alpha_0 + \alpha_1 RelAdv_{jt}^{subject} + \boldsymbol{X}_{jt}\boldsymbol{B}_x + \boldsymbol{Z}_{jt}\boldsymbol{B}_z + \theta_s + \theta_t + \epsilon_{jt},$$

where $RelAdv_{jt}^{subject}$ is an indicator variable representing a teacher with a relative advantage for teaching SWDs. Like the analysis from *Research Question 4*, we check the robustness of our results across different definitions of relative advantage for instructing SWDs.

Results

Panel A of Table 8 describes the relationship between the probability that a teacher leaves the district and teacher VAMs. The first column shows the regression results for Equation (6) but only includes SWD math VAMs. We find that teachers with higher SWD math VAMs leave the school district at a lower rate than average. Increasing a teacher's SWD math VAM by one SD is associated with a lower probability of leaving LAUSD by 0.20 percentage points. Since the average probability of any teacher leaving the district is 2.06 percent, this finding represents about 9.7 percent of the mean. The second column analyzes the relationship between non-SWD math VAMs and teachers leaving LAUSD, and we find similar results to the first column. That is, for each one SD increase in a teacher's non-SWD math VAM, the teacher's likelihood of leaving the district decreases by 0.26 percentage points on average. The third column analyzes Equation (6) which includes both student group VAMs. While the non-SWD math VAM result remains similar, the finding for SWD math VAMs is statistically insignificant. For ELA, we find a negative association between higher non-SWD VAMs and teachers leaving the district, but do not find any relationship for SWD VAMs. Overall, these results indicate that LAUSD retains teachers effective at instructing non-SWDs. We repeat this analysis using an indicator for whether a teacher switches schools within the district in online Appendix Table A4. In general, we do not find much evidence of a relationship between VAMs and switching schools. The lone exception is that we find that teachers with higher non-SWD math VAMs tend to switch schools at lower rates than average teachers.

In Panel B of Table 8, we analyze Equation (7) which uses a measure of relative advantage as the regressor. We do not find any strong relationships between relative advantage and the likelihood of teachers leaving the district. While the effect found in column (4) suggests a significant relationship between relative ELA advantage and increased likelihood of leaving LAUSD, this finding is not robust to more strict definitions of relative advantage. Panel B on online Appendix Table A4 presents the relationships between relative advantage and teachers' likelihood of switching schools. Our estimates suggest that math teachers with a relative advantage (defined either with the 10- or 20-percentile threshold) in teaching SWDs are 0.69 percentage points more likely to switch schools than their peers, while ELA teachers with a relative advantage do not have a strong relationship with switching schools.

Discussion

In this study, we seek to understand whether teachers are differentially effective at producing academic gains for students with and without disabilities. We also explore whether SWDs are more likely to be assigned to teachers who are more effective at supporting them and whether teachers who are differentially effective for SWDs stay in LAUSD. The question of whether a teacher is differentially effective with one student subgroup over another seems relatively straightforward, but we know of no previous studies that have provided empirical data to inform this question with respect to students with disabilities. One challenge is having a sufficiently large longitudinal sample in order to calculate – with reasonable precision – estimates of teachers' effectiveness within each group. We address this by using data from the Los Angeles Unified School District from 2007-2008 to 2017-2018. A second challenge in examining differential effectiveness is distinguishing between signal and noise. When calculating two different VAMs for the same teacher, it is hard to know whether the results are attributable to differences in effectiveness or whether they reflect measurement error. To address this concern, we calculated differences in VAMs based on randomly assigned SWDs and non-SWDs, giving us some sense of whether differences in effectiveness that we see in our data are wider or narrower than those we would expect to see by chance.

We have several key findings. First, we establish that teachers are differentially effective at supporting SWDs. Teachers who are effective at teaching non-SWDs are not synonymous with teachers who are best able to support SWDs. Indeed, we show that a sizeable share of the top performing teachers for non-SWDs have relatively poor performance for SWDs (as measured by VAMs). Second, we started with the assumption that it may be preferable for principals to identify which teachers have an advantage in teaching specific student groups when making classroom assignments. Hence, we consider whether our VAMs for each group are related to observable teacher characteristics. Unfortunately, there does not seem to be any relationship between either SWD or non-SWD VAMs and teacher education, experience, or credentials. Third, we find that SWDs have teachers with lower VAMs on average. These findings are consistent across both subjects and VAM types. Fourth, we turn to considering how students sort to teachers based on relative advantage. If some teachers are particularly effective with SWDs, we would ideally see that there is some sorting of SWDs into their classrooms. While we find that SWDs tend to sort to lower performing teachers overall, relative to non-SWDs, we find that SWDs are slightly more likely to have a teacher who is more effective at teaching SWDs than non-SWDs in ELA courses – e.g., she has a relative advantage teaching SWDs. In other words, for ELA courses, SWDs are likely to have lower VAM teachers, but these teachers do appear to be more effective with their SWDs than their non-SWDs. This pattern strengthens to include both subjects when we analyze the relative advantage measure within a school. This suggests that SWDs in LAUSD sort in a way that, while having lower performing teachers, nonetheless exhibits some efficiency benefits.

Overall, the results suggest that SWDs end up with relatively lower performing teachers regardless of how we measure value-added. Consistent with existing literature (e.g., Goldhaber et al., 2011; Hanushek et al., 2016), high non-SWD VAM teachers are *less* likely to leave LAUSD than low VAM teachers. However, we do not find evidence of a relationship between SWD VAM and teachers leaving the district. Thus, only the most effective teachers for students without disabilities are more likely to be retained. The remaining challenges are retaining teachers who are effective at teaching SWDs and ensuring that students with disabilities gain access to those teachers.

Collectively, how should we think about these results? Schools face a legal mandate to ensure that they are promoting equitable outcomes for students with disabilities (*Endrew F. vs. Douglas County School District RE-1,* 2017). It is essential that schools have the information necessary to ensure that SWDs are being assigned to teachers most likely to promote positive academic achievement. As our study demonstrates, overall VAMs likely do not provide enough information to inform this question. SWD-specific VAMs may be more suitable for identifying which teachers have a history of effectiveness with SWDs and whether students are being optimally assigned to these teachers. We see some evidence that SWDs are being assigned to teachers who are differentially effective at supporting this student subgroup. One silver lining is that these decisions have been made absent of the kinds of SWD-specific information we include in this study. However, there remains room for improvement. Moving forward, we encourage schools, districts, and policymakers to consider how data systems might be organized to inform a more systematic and efficient assignment of SWDs to teachers who are most likely to promote equitable academic outcomes**.**

[1] Research has documented that observation tools commonly used in general education may not capture practices known to support students with disabilities (Jones et al., 2022; Morris-Mathews et al., 2021).
[2] Over 60% of SWDs spend 80% or more of their school time in general education (U.S. Department of Education, 2018).
[3] For example, a teacher who is in the 30th percentile of the non-SWD VAM distribution but in the 45th percentile of the SWD VAM distribution would have a relative advantage in teaching SWDs even though she is below the median in both distributions (and hence is at an absolute disadvantage).
[4] In academic year 2014, California changed standardized testing regimes from the California Standards Test (CST) to the Smarter Balanced Assessment System (SBA). The CST exams were administered to students in grades 2 through 11.
[5] The term "mainstream" refers to the inclusion of students with disabilities into the general education classroom setting, as opposed to placing SWDs in a separate learning environment.
[6] SWDs (non-SWDs) paired with the same teacher across multiple years would contribute multiple observations to the total number of SWD (non-SWD) observations for that teacher.
[7] Test scores were standardized prior to dropping students who attended alternative, Community Day, and Special Education Center schools. For this reason, the presented test score average may not equal zero in our sample.
[8] These three subgroups also reflect student populations for whom we would expect varying levels of teacher differential effectiveness. For example, students with SLD typically benefit from differentiated instruction, whereas students with LSI do not.
[9] Other Disability includes the following disabilities: Deafness, Orthopedic Impairment, Deaf-Blindness, Other Health Impairment, Emotional Disturbance, Established Medical Disability (3-5 years), Hard of Hearing, Traumatic Brain Injury, Intellectual Disability, and Visual Impairment
[10] This model shrinks estimates using the autocovariance of mean test score residuals across years, which weighs more recent years more heavily compared to years that are further away from *t*.
[11] We use a Wald test to determine if any differences found between the coefficients for each teacher race across VAM types are statistically significant. P-values for the differences in the math SWD VAM and non-SWD VAM coefficients are 0.0027, 0.0000, and 0.1856 for Asian, Black, and Latino/a, respectively.
[12] We conduct a similar analysis to Table 4 using three different samples in online Appendix Table A1. In this analysis, we vary the minimum number of student observations that a teacher must have for each student group (SWD, non-SWD) for a subject. We find similar results across all samples, so henceforth, we only show results using a 10-student minimum.
[13] Teachers that leave the district due to reduction in force (layoffs) are excluded from the leave LAUSD analysis. Also, we exclude teachers that leave the district from the switch school analysis.

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Tables & Figures

Table 1: Student and Teacher Descriptive Characteristics

Panel A: Student	SWD	Autism	SLD	LSI	Other Disability	FRL	EL	Female	Asian	Black	Latino/a	White	Other Race	Math Test	ELA Test
Student	0.107	0.008	0.071	0.012	0.023	0.848	0.266	0.494	0.041	0.088	0.738	0.103	0.030	0.057	-0.006
N = 661,789	(0.309)	(0.092)	(0.257)	(0.110)	(0.150)	(0.359)	(0.442)	(0.500)	(0.198)	(0.283)	(0.440)	(0.304)	(0.170)	(0.966)	(0.944)
Student-Year															
Non-SWD	0.000	0.000	0.000	0.000	0.000	0.785	0.182	0.511	0.043	0.074	0.745	0.107	0.032	0.126	0.078
N = 1,465,535	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.411)	(0.386)	(0.500)	(0.202)	(0.262)	(0.436)	(0.309)	(0.176)	(0.992)	(0.951)
SWD	1.000	0.081	0.679	0.094	0.202	0.809	0.418	0.349	0.019	0.096	0.756	0.111	0.018	-0.577	-0.692
N = 158,373	(0.000)	(0.273)	(0.467)	(0.291)	(0.402)	(0.393)	(0.493)	(0.477)	(0.135)	(0.294)	(0.429)	(0.315)	(0.133)	(0.852)	(0.865)
Autism	1.000	1.000	0.058	0.018	0.049	0.646	0.222	0.144	0.066	0.078	0.562	0.251	0.043	-0.067	-0.157
N = 12,877	(0.000)	(0.000)	(0.233)	(0.131)	(0.217)	(0.478)	(0.416)	(0.351)	(0.248)	(0.268)	(0.496)	(0.433)	(0.204)	(1.030)	(1.000)
SLD	1.000	0.007	1.000	0.026	0.036	0.848	0.498	0.395	0.011	0.086	0.817	0.073	0.013	-0.740	-0.878
N = 107,512	(0.000)	(0.083)	(0.000)	(0.159)	(0.185)	(0.359)	(0.500)	(0.489)	(0.104)	(0.280)	(0.387)	(0.261)	(0.112)	(0.740)	(0.747)
LSI	1.000	0.015	0.187	1.000	0.060	0.807	0.330	0.260	0.032	0.086	0.745	0.116	0.022	-0.103	-0.234
N = 14,836	(0.000)	(0.122)	(0.390)	(0.000)	(0.238)	(0.395)	(0.470)	(0.439)	(0.175)	(0.280)	(0.436)	(0.320)	(0.146)	(0.967)	(0.967)
Other Disability	1.000	0.020	0.119	0.028	1.000	0.760	0.267	0.296	0.019	0.138	0.639	0.179	0.024	-0.472	-0.511
N = 32,068	(0.000)	(0.140)	(0.324)	(0.164)	(0.000)	(0.427)	(0.443)	(0.457)	(0.137)	(0.345)	(0.480)	(0.384)	(0.153)	(0.883)	(0.901)
Panel B: Teacher			Experience												
	SpEd Credential	Master's or PhD	Novice (1-2 yrs)	Early (3-5 yrs)	Middle (6-10 yrs)	Late (10+ yrs)		Female	Asian	Black	Latino/a	White	Other Race		
Teacher-Year	0.015	0.364	0.022	0.063	0.150	0.766		0.694	0.087	0.097	0.390	0.392	0.034		
N = 45,139	(0.122)	(0.481)	(0.145)	(0.243)	(0.357)	(0.424)		(0.461)	(0.282)	(0.296)	(0.488)	(0.488)	(0.180)		

A student's status for a characteristic may change across years. The first row represents the percent of students that have ever been indicated with the respective status (except test scores, which represent means). Remaining rows indicate student-year observations pooled across SY 2007-08 to SY 2017-18. Sample contains students paired with teachers with at least 10 SWD and non-SWD observations across the dataset. SWD (student with disability). SLD (specific learning disability). LSI (language & speech impairment). FRL (free or reduced-price lunch). EL (English learner). SpEd (special education).

Table 2: Share of Teachers by Descriptive Characteristics, Varying Minimum Threshold of Students

Threshold Sample	≤5 (Out)	≥6	≥10	≥15
SpEd Credential	19%	1%	1%	2%
Master's or PhD	38%	37%	36%	36%
Exp: Novice (1-2 yrs)	7%	2%	2%	2%
Exp: Early (3-5 yrs)	9%	6%	6%	6%
Exp: Mid (6-9 yrs)	16%	15%	15%	15%
Exp: Late (10+ yrs)	68%	76%	77%	77%
Female	73%	70%	69%	68%
Asian	10%	9%	9%	9%
Black	13%	10%	10%	9%
Latino/a	35%	39%	39%	39%
White	38%	39%	39%	40%
Other Race	4%	3%	3%	3%

Threshold samples contain teachers with at least the given threshold quantity (i.e., 6, 10, or 15) of SWD and non-SWD observations across the panel dataset. Data are at teacher-year level. Out of sample teacher-years teach 33% of student-year observations. SpEd (special education). Exp (years of experience). SWD (student with disability).

Table 3: Teacher Distribution of SWD and Non-SWD VAMs by Quintile

Panel A: Math		Non-SWD VAM Quintiles				
		1	2	3	4	5
	1	**9.0%**	5.2%	3.2%	1.7%	0.9%
SWD	2	5.0%	**5.5%**	4.6%	3.2%	1.7%
VAM	3	3.3%	4.5%	**4.9%**	4.4%	2.9%
Quintiles	4	2.0%	3.3%	4.5%	**5.6%**	4.7%
	5	0.7%	1.5%	2.9%	5.1%	**9.8%**
Panel B: ELA		**Non-SWD VAM Quintiles**				
		1	2	3	4	5
	1	**7.4%**	5.0%	3.8%	2.6%	1.3%
SWD	2	5.0%	**4.8%**	4.3%	3.6%	2.3%
VAM	3	3.6%	4.6%	**4.4%**	4.0%	3.4%
Quintiles	4	2.6%	3.4%	4.2%	**5.0%**	4.7%
	5	1.4%	2.3%	3.3%	4.9%	**8.2%**

Each teacher year observation is assigned to a quintile by its relative rank in the VAM distribution. The lowest quintile of VAMs is represented by 1, and the highest quintile of VAMs is represented by 5. Observations are at the teacher-year level. 34,373 total math observations. 35,197 total ELA observations. SWD (student with disability). VAM (value-added measure). ELA (English language arts).

Table 4: Association between Teacher Characteristics and SWD and non-SWD VAMs

	Math VAM		ELA VAM	
	(1) SWD	(2) Non-SWD	(3) SWD	(4) Non-SWD
SpEd Credential	-0.182	-0.188	-0.002	-0.068
	(0.094)	(0.107)	(0.094)	(0.071)
Master's or PhD	-0.009	-0.024	0.062*	0.022
	(0.026)	(0.025)	(0.025)	(0.024)
Exp: Early Career (3-5 yrs)	0.002	0.109**	0.033	0.032
	(0.038)	(0.040)	(0.038)	(0.043)
Exp: Middle Career (6-9 yrs)	0.015	0.074	0.026	0.007
	(0.045)	(0.042)	(0.044)	(0.044)
Exp: Late Career (10+ yrs)	-0.131**	-0.063	-0.015	-0.015
	(0.048)	(0.044)	(0.042)	(0.043)
Female	0.031	0.097**	0.018	0.211***
	(0.031)	(0.030)	(0.029)	(0.030)
Asian	0.140**	0.170***	-0.072	0.060
	(0.047)	(0.045)	(0.047)	(0.045)
Black	-0.101*	-0.271***	-0.054	-0.253***
	(0.048)	(0.050)	(0.040)	(0.042)
Latino/a	0.077*	0.068*	0.032	0.031
	(0.034)	(0.033)	(0.030)	(0.031)
Other Race	0.045	-0.015	-0.056	-0.035
	(0.070)	(0.065)	(0.068)	(0.073)
N	34,373	34,373	35,197	35,197

School-clustered standard errors shown in parentheses. All columns include school and year fixed effects and classroom demographic characteristics. Novice teachers (1-2 yrs) are excluded experience group. White teachers are excluded racial/ethnic group. SWD (student with disability). VAM (value-added measure). ELA (English language arts). SpEd (special education). Exp (years of experience). *p<.05. **p<.01. ***p<.001.

Table 5: Association between Student Disability Status and Teacher VAMs

	Math VAM		ELA VAM	
	(1) SWD	(2) Non-SWD	(3) SWD	(4) Non-SWD
SWD	-0.036***	-0.043***	-0.040***	-0.056***
	(0.005)	(0.004)	(0.006)	(0.004)
N	1,408,173	1,408,173	1,481,418	1,481,418

Teacher-clustered standard errors shown in parentheses. All columns include school-grade-year fixed effects. SWD (student with disability). VAM (value-added measure). *p<.05. **p<.01. ***p<.001.

Table 6: Association between Student Disability Status and Teacher VAMs

Panel A: FRL	Math VAM		ELA VAM	
	(1) SWD	(2) Non-SWD	(3) SWD	(4) Non-SWD
FRL	-0.034***	-0.040***	-0.036***	-0.048***
	(0.007)	(0.005)	(0.007)	(0.005)
SWD	-0.041***	-0.053***	-0.059***	-0.081***
	(0.010)	(0.008)	(0.010)	(0.007)
FRL × SWD	0.008	0.013	0.024*	0.032***
	(0.009)	(0.007)	(0.009)	(0.007)
Sum of coeffs.	-0.067***	-0.080***	-0.071***	-0.097***
	(0.010)	(0.007)	(0.010)	(0.007)
Panel B: EL	**Math VAM**		**ELA VAM**	
	(1) SWD	(2) Non-SWD	(3) SWD	(4) Non-SWD
EL	-0.047***	-0.058***	-0.020	-0.062***
	(0.009)	(0.007)	(0.011)	(0.008)
SWD	-0.041***	-0.051***	-0.044***	-0.068***
	(0.006)	(0.005)	(0.007)	(0.005)
EL × SWD	0.037***	0.050***	0.019*	0.061***
	(0.007)	(0.006)	(0.008)	(0.006)
Sum of coeffs.	-0.051***	-0.059***	-0.045***	-0.069***
	(0.008)	(0.007)	(0.011)	(0.008)
Panel C: Non-white, non-Asian	**Math VAM**		**ELA VAM**	
	(1) SWD	(2) Non-SWD	(3) SWD	(4) Non-SWD
Non-white, non-Asian	-0.057***	-0.071***	-0.060***	-0.085***
	(0.010)	(0.008)	(0.010)	(0.008)
SWD	-0.061***	-0.067***	-0.065***	-0.091***
	(0.013)	(0.010)	(0.012)	(0.008)
Non-white, non-Asian × SWD	0.030*	0.029**	0.029*	0.042***
	(0.012)	(0.009)	(0.011)	(0.008)
Sum of coeffs.	-0.087***	-0.109***	-0.096***	-0.134***
	(0.012)	(0.009)	(0.013)	(0.010)
N	1,408,173	1,408,173	1,481,418	1,481,418

Teacher-clustered standard errors shown in parentheses. All columns include school-grade-year fixed effects. *Sum of coeffs.* row shows the difference in VAM for a SWD with the specific characteristic and a non-SWD that does not fall into the given category. SWD (student with disability). VAM (value-added measure). FRL (free or reduced-price lunch). EL (English learner). *p<.05. **p<.01. ***p<.001.

Table 7: Association between Student Disability Status and Teacher Relative Advantage

Panel A: SWD sorting to teachers with relative advantage toward instructing SWDs						
	Math			ELA		
Relative Advantage Definition	(1) >0	(2) >10	(3) >20	(4) >0	(5) >10	(6) >20
SWD	0.004	0.004	0.003	0.007**	0.008**	0.006**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
N	1,408,173	1,408,173	1,408,173	1,481,418	1,481,418	1,481,418

Panel B: SWD sorting to teachers below median DVAM *within* school-grade-year		
	Math	ELA
	(1)	(2)
SWD	0.007**	0.010***
	(0.002)	(0.003)
N	1,408,173	1,481,418

In Panel A, the outcome variable is a dummy indicator for relative advantage. >0 (>10; >20) indicate that the SWD VAM percentile is more than 0 (10; 20) percentile points greater than the non-SWD VAM percentile. In Panel B, the outcome is a dummy indicator for teachers whose DVAMs are strictly less than the median DVAM of all teachers within a given school-grade-year combination. Teacher-clustered standard errors shown in parentheses. All columns include school-grade-year fixed effects. SWD (student with disability). ELA (English language arts). VAM (value-added measure). *p<.05. **p<.01. ***p<.001.

Table 8: VAMs and Relative Advantage Association with Leaving LAUSD

Panel A: VAM	Math			ELA		
	(1)	(2)	(3)	(4)	(5)	(6)
SWD VAM	-0.0020**		-0.0008	-0.0005		0.0003
	(0.0006)		(0.0007)	(0.0006)		(0.0007)
Non-SWD VAM		-0.0026***	-0.0022**		-0.0020**	-0.0021**
		(0.0006)	(0.0007)		(0.0006)	(0.0007)
Panel B: Relative Advantage	**Math**			**ELA**		
	(1)	(2)	(3)	(4)	(5)	(6)
Relative Advantage (RA)	0.0025	0.0012	0.0007	0.0031*	0.0026	0.0028
	(0.0014)	(0.0016)	(0.0018)	(0.0014)	(0.0016)	(0.0017)
RA Definition	>0	>10	>20	>0	>10	>20
N	34,355	34,355	34,355	35,154	35,154	35,154

Leave LAUSD is a dummy indicator that equals 1 when a teacher leaves Los Angeles Unified School District at the end of the academic year. Relative advantage variables are dummy indicators that equal 1 when a teacher has a SWD VAM percentile > non-SWD VAM percentile for a given year in that subject. >0 (>10; >20) indicate that the SWD VAM percentile is more than 0 (10; 20) percentile points greater than the non-SWD VAM percentile. Teachers that leave due to reduction in force are excluded. Teacher-clustered standard errors shown in parentheses. All columns include school and year fixed effects. Coefficients for teacher and class characteristics not shown. VAM (value-added measure). SWD (student with disability). ELA (English language arts). RA (relative advantage). *p<.05. **p<.01. ***p<.001.

Figure 1: Comparison of Teacher SWD and non-SWD VAMs

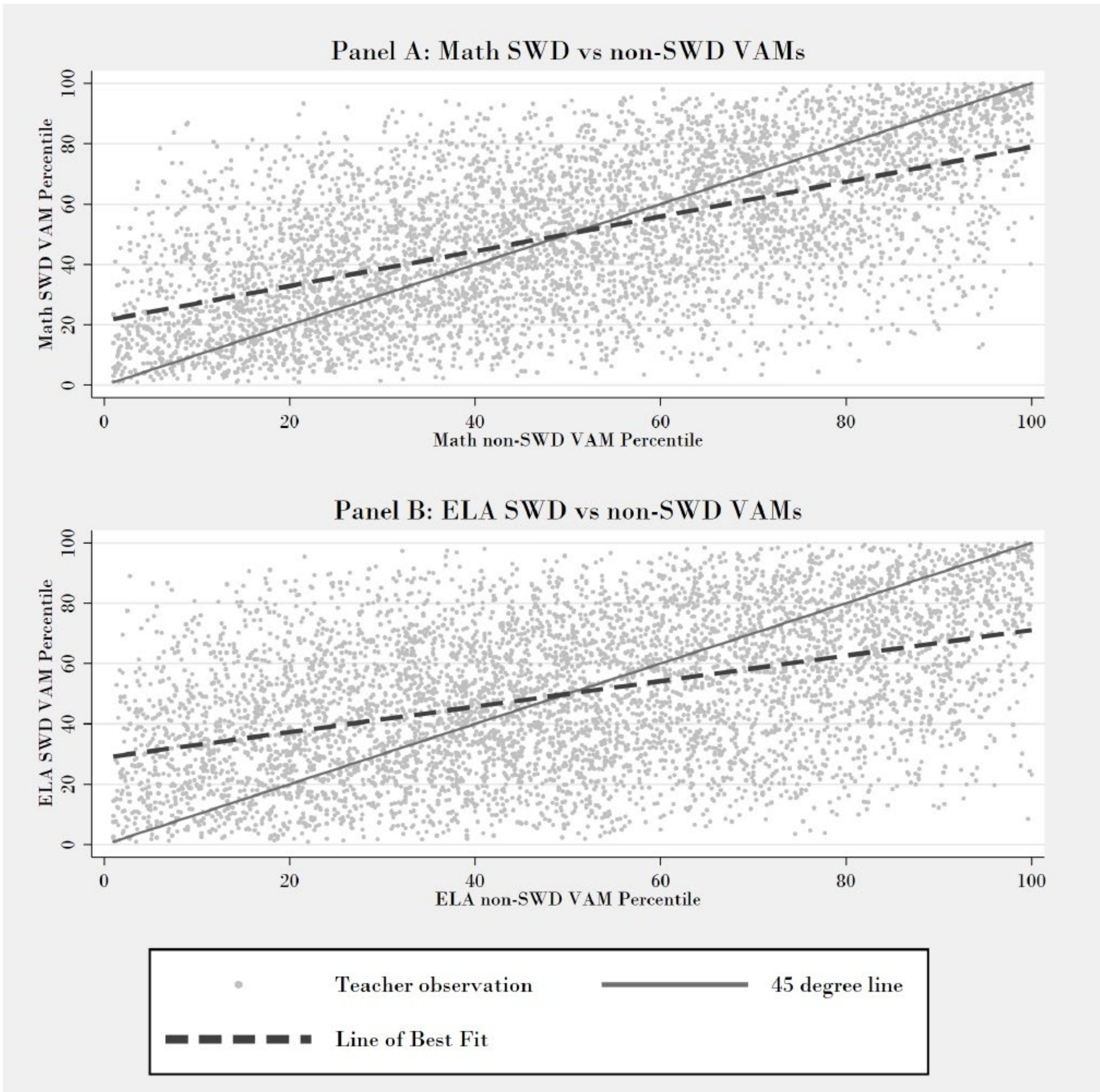

Figure 2: DVAM distribution compared to Randomized DVAM distribution

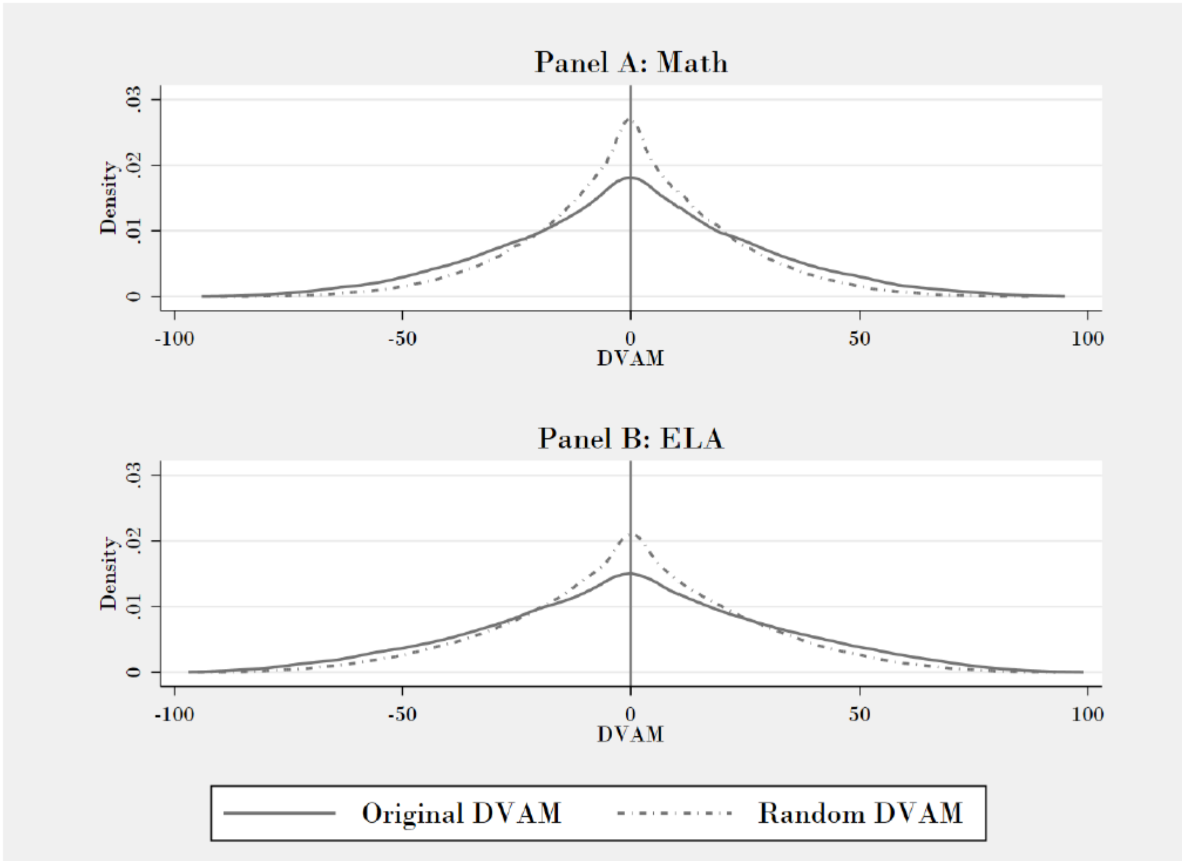

Figure Notes

1. *Note.* Observations at the teacher level. Math best fit line slope = 0.58. ELA best fit line slope = 0.42. Teacher VAMs shown are averaged across years. VAM (value-added measure). SWD (student with disability). ELA (English language arts).
2. *Note.* This figure compares the DVAM distribution of our sample to the DVAM distribution generated when randomly assigning student with disability (SWD) status within each classroom. DVAM represents the difference in a teacher's percentile ranking in SWD VAM from their percentile ranking in non-SWD VAM. A negative DVAM indicates a relative advantage for instructing SWDs. Since the randomization process preserves the number of SWDs and non-SWDs within each classroom, the *Random DVAM*s use an identical sample as their *Original DVAM* analogue.

A1. *Note.* This figure compares the DVAM distribution of our sample to the DVAM distribution generated when randomly assigning student with disability (SWD) status within each classroom, where DVAM represents the difference in a teacher's percentile ranking in SWD VAM from their percentile ranking in non-SWD VAM. A negative DVAM indicates a relative advantage for instructing SWDs. The numbers within the legend signify the threshold samples used in generating the VAMs. For example, *Original DVAM 6* was created using only teachers with at least 6 SWDs and at least 6 non-SWDs across the panel. Since the randomization process preserves the number of SWDs and non-SWDs within each classroom, the *Random DVAM*s uses an identical sample as the *Original DVAM* analogue.

Online Appendix – Not for Publication

Table A1: Association between Student Disability Status and Teacher VAMs by Threshold Sample

Panel A: Math	SWD VAM			Non-SWD VAM		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	6	10	15	6	10	15
SWD	-0.036***	-0.036***	-0.035***	-0.042***	-0.043***	-0.041***
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)
N	1,582,059	1,408,173	1,174,409	1,582,059	1,408,173	1,174,409
Panel B: ELA	**SWD VAM**			**Non-SWD VAM**		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	6	10	15	6	10	15
SWD	-0.044***	-0.040***	-0.037***	-0.056***	-0.056***	-0.054***
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)
N	1,664,316	1,481,418	1,246,446	1,664,316	1,481,418	1,246,446

Threshold samples contain students taught by teachers with at least the given threshold quantity (i.e., 6, 10, or 15) of SWD and non-SWD observations across the panel dataset. Teacher-clustered standard errors shown in parentheses. All columns include school-grade-year fixed effects. VAM (value-added measure). SWD (student with disability). ELA (English language arts). *p<.05. **p<.01. ***p<.001.

Table A2: Association between Student Disability Type and Teacher VAMs

	Math VAM		ELA VAM	
	(1) SWD	(2) Non-SWD	(3) SWD	(4) Non-SWD
Autism	-0.006	0.005	-0.006	-0.012*
	(0.007)	(0.006)	(0.008)	(0.006)
SLD	-0.041***	-0.053***	-0.051***	-0.065***
	(0.006)	(0.005)	(0.007)	(0.005)
LSI	-0.006	-0.001	0.004	0.002
	(0.005)	(0.004)	(0.005)	(0.005)
Other Disability	-0.026***	-0.030***	-0.023***	-0.043***
	(0.006)	(0.004)	(0.005)	(0.004)
N	1,408,173	1,408,173	1,481,418	1,481,418

Teacher-clustered standard errors shown in parentheses. All columns include school-grade-year fixed effects. SWD (student with disability). VAM (value-added measure). SLD (specific learning disability). LSI (language and speech impairment). *p<.05. **p<.01. ***p<.001.

Table A3: Association between Student Disability Type and Teacher Relative Advantage

	Math			ELA		
Relative Advantage Definition	(1) >0	(2) >10	(3) >20	(4) >0	(5) >10	(6) >20
Autism	-0.004	-0.003	-0.001	0.003	0.002	-0.000
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
SLD	0.006*	0.006*	0.004	0.007*	0.009**	0.006*
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
LSI	-0.007**	-0.003	-0.002	0.002	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Other Disability	0.005*	0.003	0.003	0.010***	0.008**	0.008***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
N	1,408,173	1,408,173	1,408,173	1,481,418	1,481,418	1,481,418

Outcome variables are dummy indicators for relative advantage. >0 (>10; >20) indicate that the SWD VAM percentile is more than 0 (10; 20) percentile points greater than the non-SWD VAM percentile. Teacher-clustered standard errors shown in parentheses. All columns include school-grade-year fixed effects. ELA (English language arts). SLD (specific learning disability). LSI (language and speech impairment). VAM (value-added measure). *p<.05. **p<.01. ***p<.001.

Table A4: VAMs and Relative Advantage Association with Switching Schools within LAUSD

Panel A: VAM	Math			ELA		
	(1)	(2)	(3)	(4)	(5)	(6)
SWD VAM	-0.0023		0.0010	0.0008		0.0019
	(0.0014)		(0.0017)	(0.0014)		(0.0015)
Non-SWD VAM		-0.0057***	-0.0063***		-0.0020	-0.0028
		(0.0014)	(0.0016)		(0.0014)	(0.0015)
Panel B: Relative Advantage	Math			ELA		
	(1)	(2)	(3)	(4)	(5)	(6)
Relative Advantage (RA)	0.0047	0.0069*	0.0069*	0.0035	0.0056	-0.0014
	(0.0028)	(0.0030)	(0.0034)	(0.0028)	(0.0030)	(0.0033)
RA Definition	>0	>10	>20	>0	>10	>20
N	33,748	33,748	33,748	34,489	34,489	34,489

Switch school is a dummy indicator that equals 1 when a teacher changes schools within Los Angeles Unified School District the following year. Relative advantage variables are dummy indicators that equal 1 when a teacher has a VAM SWD percentile > VAM non-SWD percentile for a given year in that subject. >10 (>20) indicate that the VAM SWD percentile is more than 10 (20) percentile points greater than VAM non-SWD percentile. Teachers that leave due to reduction in force are excluded. Teacher-clustered standard errors shown in parentheses. All columns include school and year fixed effects. Coefficients for teacher and class characteristics not shown. VAM (value-added measure). SWD (student with disability). ELA (English language arts) RA (relative advantage). *p<.05. **p<.01. ***p<.001.

Figure A1: DVAM distribution compared to Randomized DVAM distribution by Threshold Sample