**** PRELIMINARY DRAFT****

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Are Effective Teachers for Students with Disabilities Effective Teachers for All?[1]

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Students with disabilities make up approximately 14% of the K-12 student population, and over 60 percent of these students spend 80 percent or more of their time in school in the general education classroom setting (National Center for Education Statistics, 2018, Table 204.60). At the same time, many general educators are not suitably prepared to support students with disabilities (SWD; e.g., Brownell, Sindelar, Kiely, & Danielson, 2010; Cook, 2002; Sindelar, Brownell, & Billingsley, 2010). Only seven states require general education teachers (GETs) to complete coursework for working with SWDs, and only two require clinical experiences working with these students (Galiatsos, Kruse, & Whittaker, 2019). Existing studies suggest that GETs receive minimal coverage of special education teaching methods in their coursework and have few practice opportunities focused on SWDs (Blanton, Pugach & Florian, 2011; Blanton, Pugach, & Boveda, 2018; Florian, 2012; Galiatsos, Kruse, & Whittaker, 2019).

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And surveys of general educators routinely find that many of them feel underprepared to support the diverse educational needs of SWDs (e.g. Kamens, Loprete, and Slostad, 2000; Sadler, 2005).

At the same time, SWDs perform worse on math and reading achievement assessments than do their nondisabled peers (e.g., Chudowsky et al., 2009; Schulte et al., 2016). Thus, a substantial subset of K-12 students is assigned to teachers who feel underprepared to support their learning needs, and possibly as a result, continue to underperform on state assessments. One potential solution to this problem is to identify teachers within each school who are more effective at supporting SWDs than their peers. That some teachers may be differentially effective with varying groups of students (e.g., low- or high-achieving, female or male, or English learners) is not a new concept (Aaronson, Barrow, & Sander, 2007; Lockwood & McCaffery, 2009; Dee, 2007). Indeed, Loeb, Soland, & Fox (2014) and Master, et al. (2016) have documented that teachers are differentially effective at improving academic outcomes for English language learners, and that prior experiences and training are both predictive of teachers' success in supporting these students' academic growth. To date, however, no such studies have been conducted focusing on SWDs.

Why might some teachers be better at teaching SWDs? There is ample evidence that students with weaker prior academic skills benefit from explicit, systematic instruction in reading and mathematics, where the teacher takes an active role in shaping students' learning experiences (e.g., Connor et al., 2011; Connor et al., 2018; Gersten et al., 2009a, b; Stockard et al., 2014; Torgesen, 2001). Specifically for SWDs, research has documented that effective practices for instructing SWDs utilize intensive instruction that focus on fewer and higher priority skills and concepts (Gersten et al., 2009a, b; Torgesen, 2001).

Unfortunately, the tools we use to measure teacher effectiveness do not always reflect the reality that teachers have skills specific to different types of students. For both class-wide student growth measures and other common evaluation metrics like observation systems, the underlying assumption is that good teaching can be measured via an average; that 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.[2] However, research on teaching and learning suggests that to effectively meet the needs of all of their students, teachers need to tailor their instruction to the students in their class. To date, research on teacher effectiveness has largely ignored this nuance, instead focusing on a teacher's ability to meet the needs of the average student. By not disaggregating overall metrics of teacher effectiveness, we will be hampered in our ability to focus on the true quality of teachers for a critical sub-population of students.

To test the relative effectiveness of general education teachers towards SWDs, we leverage Los Angeles Unified School District (LAUSD) administrative data from SY 2007-2008 through SY 2017-2018 and disaggregate overall value-added measures of teacher effectiveness (VAMs) into two measures: one focusing on teachers' effectiveness in improving outcomes for SWDs and one examining VAMs for their non-SWDs. We capitalize on these longitudinal data to generate two different sets of time-invariant value-added measures for each teacher: a SWD VAM and a non-SWD VAM. Using these two measures, we explore the following research questions:

1. Do some teachers have a relative advantage in teaching SWD versus non-SWD students?

[2] Research has documented that observation tools commonly used in general education may not capture practices known to support SWDs (Jones & Brownell, 2014; Morris-Mathews et al., 2020).

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. Are SWDs sorted to teachers with higher/lower SWD VAMs?
4. Are schools retaining teachers with higher SWD VAMs or non-SWD VAMs?

We conceive of a teacher having a relative advantage in teaching SWDs (relative to non-SWDs) if their VAM score is higher in the distribution of teacher effectiveness within the district for SWDs than it is in the non-SWD teacher effectiveness (VAM) distribution.

This study contributes to the literature in several ways. First, we document whether teachers are similarly effective at teaching students based on their disability status. Second, there is a long literature that explores whether observable teacher characteristics are associated with more effective teachers (e.g. Kane et al., 2008). We contribute to this literature by conducting 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' relative advantage. Placing SWDs in classrooms where teachers exhibit a relative advantage at instructing SWDs can potentially raise the test scores of these students more efficiently, but only if schools are able to retain these teachers.

Data

Context

We use data from the Los Angeles Unified School District (LAUSD), the second-largest school system in the United States. As of 2018, LAUSD enrolled over 580,000 students in grades

K-12 with over 24,000 K-12 teachers.[3] The LAUSD administrative data contain extensive, 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 60% of students with mild or moderate disabilities spend most of their days in general education classrooms (Swaak, 2020). The decision of whether a student should be included in general education is made on a case-by-case basis by a team of school personnel and outside professionals, in collaboration with parents and driven by the child's individualized needs. Then, among SWDs who are educated in the general education classroom, placement procedures into specific teachers' classrooms are decided by school personnel. Many students with mild to moderate disabilities can function effectively within a general education setting with accommodations.

Sample

This study uses student- and teacher-level matched administrative data from SY2007-2008 through SY2017–2018, provided by LAUSD's Office of Data and Accountability and the Division of Human Resources. Our sample includes all third through 8th-grade students attending mainstream public schools. 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), and English Language Learner (ELL) status, as well as state standardized math and English Language Arts (ELA) test scores for students in Grades 3 through 8. We normalize each subject's test scores to have a mean of zero and standard deviation of one

[3] http://achieve.lausd.net/facts/2020

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 order to compare teachers' non-SWD VAMs relative to their SWD VAMs, our analytic dataset is limited to general education classrooms. To be included in the analytical sample, teachers must have at least six unique student-year pairings with non-SWDs and an additional six unique student-year pairings with SWDs, totaling to at least 12 unique student-year pairings between SY 2007-08 and 2017-18. Given these restrictions, we observe 646 unique schools, 6300 unique teachers, and 698,458 unique students. The data also yield 1,788,510 unique student-year observations within grades three through eight.

Table 1 shows the analytical sample pooled across the 11 years of the longitudinal dataset. The first row of Table 1 contains the demographic and standardized test information of all students in our dataset. Since many student demographic characteristics change over time (e.g., SWD, FRL, ELL, etc.), the interpretation of student characteristics for this row is the percent of students to have ever been classified for the specific characteristic. For example, 10% of the students within our sample have ever been classified as SWDs during the time we observe them. Test scores are interpreted as the average test score for all students.[4] Students may have multiple types of disabilities; the disability categories *Autism*, *SLD* (specific learning disability), *LSI* (language & speech impairment), and *Other Dis.* (other disability)[5] are not mutually

[4] 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.
[5] Other Disability includes the following disabilities: Deafness, Orthopedic Impairment, Deaf-Blindness, Other Health Impairment, Emotional Disturbance, Established Medical Disability (3-5 yrs), Hard of Hearing, Traumatic Brain Injury, Intellectual Disability, and Visual Impairment

exclusive which necessitates that the sum of these columns is greater than the *SWD* column. Almost 84% of students have ever been eligible for free- or reduced-priced lunch (*FRL*), 37% have ever been classified as an English Language Learner (*ELL*), 74% of students are Latino/a, and only 10% 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 various disability subgroups.

The second and third rows separate the overall student body between non-SWDs and SWDs. This separation highlights some interesting differences between subcategories. Aside from the difference in standardized test scores, SWDs are far more likely to be ELLs and male. Of student-years classified as a SWD, 8.2% are classified under *Autism*, 68.4% under *SLD*, 8.7% under *LSI*, and 20.0% under *Other Dis*. The remaining rows highlight observable differences within SWDs by disability type.

Teachers vary in for how many years they have certain credentials or degrees. For example, a teacher may be fully credentialed for the entire of the 11-year sample, and a different teacher will have only been fully credentialed after two years of being in the sample. To try to capture this variation, we create variables prefixed with *% Time* to indicate what percent of the time a teacher possesses the characteristic within the 11-year period of our sample. *The* final row of Table 1 displays the teachers characteristics along with the *% Time* variables. On average, teachers are fully certified 76.6% of the time, have special education accreditation 0.6% of the time, have a master's degree 31.1% of the time, and change schools within LAUSD 7.5% of the time over the 11-year sample. Over 4% of teachers leave the district across the 11 years. Over 39% of teachers are Latino\a and over 38% are White.

Methods

VAM Calculations

We create two separate VAMs for each subject and for each teacher to measure their contribution to student growth on achievement tests for SWDs and for non-SWDs. We estimate the following model for each teacher separately for each subject and students' SWD status:

$$(1) \qquad Ach_{ijst} = \beta_1 Ach^{math}_{ijst-1} + \beta_2 Ach^{ela}_{ijst-1} + \boldsymbol{X}_{ijst}\boldsymbol{\theta} + \boldsymbol{T}_j\boldsymbol{\Omega} + \theta_t + \varepsilon_{ijst},$$

where *Ach* is either math or ELA achievement, standardized within test and year, for student *i* with teacher *j* in school *s* in year *t*. 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 (Chetty, Friedman, & Rockoff, 2014) and to attenuate measurement error (Lockwood & McCaffrey, 2014). $\boldsymbol{X}$ is a vector of student demographic characteristics, including indicators of student race, gender, free- or reduced-price lunch eligibility, English learner status, and grade level. Teachers' VAMs are estimated by the coefficients on a set of teacher fixed effects ($\boldsymbol{T}$). θ_t are year fixed effects, and ε is an error term. Each observation is weighted by the share of trimesters or semesters in the year during which the student-teacher link was observed. 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, Mihaly, and Rockoff (2015).

We produce shrunken estimates to reduce attenuation bias when including VAMs as independent variables and to account for uncertainty for teachers with few students or students with difficult-to-predict achievement trajectories, as is commonly done in the literature (Herrmann, Walsh, Isenberg, & Resch, 2013; Koedel et al., 2015). In practice, empirical Bayesian (EB) shrinkage moves teachers with extremely high or low VAMs towards the mean in cases where their scores are measured imprecisely (e.g. based on only a small number of students). Precisely estimated VAMs, in contrast, are shrunken to a much smaller extent. Actual shrinkage is conducted using the algorithm made public by Mathematica's Educator Impact Lab.[6]

Research Question 1: Do some teachers have a relative advantage in teaching SWD versus non-SWD students?

We begin by exploring the relationship between teachers' relative rank in SWD and non-SWD VAMs compared to other LAUSD teachers. To do this, we separate each subject and student subgroup VAM and assign the corresponding percentile fore each teacher relative to all other teachers for whom the VAM is calculated. Thus,each teacher is assigned four different values based on the percentile they fall under for each subject-VAM combination (i.e., Math-SWD, Math-NonSWD, ELA-SWD, and ELA-NonSWD). Once these values are assigned to each teacher, we compute the difference between the SWD and Non-SWD VAM percentiles for each subject. We label this statistic the Difference in VAMs (DVAM), which is defined as:

$$DVAM^{subject} = Ptile\left(VAM^{subject}_{Non-SWD}\right) - Ptile\left(VAM^{subject}_{SWD}\right), \tag{2}$$

where $Ptile\left(X^s_g\right) = \frac{Rank^s_g}{N^s_g}$ is a function that converts its argument into a percentile by dividing the teacher's within-subject (s) and group (g) rank by the total number of teachers for whom we are able to calculate a VAM in that subject and group. Using the Equation (2), we define a teacher as having a relative advantage in instructing SWDs when their DVAM is negative. That is, a teacher falls in a higher percentile in the SWD VAM distribution than in the non-SWD

[6] https://www.edimpactlab.com/programmer-resources/free-program-code

VAM distribution. Similarly, we define a teacher as having a relative advantage in teaching non-SWDs if their DVAM is positive.

A reasonable concern about the DVAMs assigned to a teacher is that VAMs can be quite noisy when estimated, 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 SWDs and non-SWDs. Specifically, we randomly assign SWD status to each student (while preserving the total size of a teacher's class) and calculate two separate VAMs by group 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 "pseudo" SWD and non-SWD VAMs would be due to random noise. Following Loeb et al. (2014) we repeat this process 75 times, and the VAMs are then averaged for each teacher. This provides each teacher with four different randomized VAMs across student group and subjects. Following Equation (2), we generate a randomized DVAM for math and another for ELA.

This exercise provides us with a baseline to assess how much of the differences we see in the original distribution is likely due to random estimation error.[7] In theory, if the differences in the two VAMs contain information beyond noise, the variation in the randomized DVAM should be steeper than the original DVAM distribution. Randomizing SWD status should keep both, the SWD VAMs and the non-SWD VAMs, near zero. Correspondingly, the difference between these two VAMs should also be nearer to zero than the actual DVAMs. Finally, the variation in the original DVAM being greater than the randomized DVAM is evidence that teachers exhibit a

[7] In future iterations we will bootstrap the exercise to account for sampling error as well.

relative advantage for different groups of students. In other words, this finding would indicate that there exist teachers that are "better" at instructing one group of students relative to their peers than the other group of students. A larger magnitude of a teacher's DVAM indicates a larger relative advantage towards a particular group of students. For example, a teacher in the 99th percentile of the SWD VAM and the 50th percentile of the non-SWD VAM would have a DVAM of 49 towards SWDs. Since each rank structure is relative to all other teachers, this particular teacher would be said to have a relative advantage in teaching SWDs as compared to their teacher peers.

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?

Most observable teacher characteristics (e.g. Master's degree, certification) do not accurately predict teacher effectiveness measured by higher VAM scores (e.g. Chingos & Peterson, 2011; Kane et al., 2008). However, it may be that observable characteristics are relatively uncorrelated with teacher VAM scores because teacher effectiveness is aggregated across multiple types of students when VAMs are created. To explore the possibility that observable characteristics of teachers can help us identify those with a relative advantage teaching SWDs (or non-SWDs), we use a standard linear regression model to estimate if observable teacher characteristics for teachers with different VAMs for each subject (math, ELA) and student type (SWD, non-SWD). Our model is as follows:

(3) $$Y_j^{subject,type} = \beta_0 + \beta_x VAM_j^{subject,type} + \epsilon_j^{subject,type} ,$$

where Y_j is the teacher characteristic of interest for teacher *j*, *subject* is either math or ELA, *type* is either SWD or non-SWD, and ϵ is an error term. VAM_j is a standardized score calculated using Equation (1) for each type and subject. $\beta_x^{subject,type}$ is the coefficient of interest and is interpreted as the association between teacher VAM (for subject and type of student) and the observable teacher characteristic. It can be interpreted as the change in the probability that a teacher is that observable characteristic (e.g., female) for a one standard deviation unit increase in the teachers' VAM. By regressing the characteristics on the VAMs, we can see whether higher VAM scores are associated with certain teacher observable characteristics. We run each regression separately for each type of VAM which allows for the uncontrolled association between VAM and characteristic. Though the results from Equation (3) are purely descriptive, they can provide valuable insight in determining if top SWD VAM teachers can be distinguished from top non-SWD VAM teachers through traditional observable characteristics. We use a Wald test to determine if the differences between $\beta_x^{sub,SWD}$ and $\beta_x^{sub,non-SWD}$ are statistically significant.

Research Question 3: Do SWDs sort into classes taught by a teacher with high VAMs? If so, does it differ by disability type?

We regress an indicator which determines whether a teacher is in the top quintile of each VAM separately on SWD status using the following equation:

$$(4) \qquad Y_{ist}^{subject,type} = \alpha_0 + \alpha_1^{subject,type} SWD_{ist} + \alpha_2^{subject,type} X'_{ist} + \theta_{st} + \epsilon_{ist},$$

where $Y^{subject,type}$ is an indicator representing a teacher being in the top quintile of the VAM distribution for a given subject (math, ELA) and type of student (SWD, non-SWD, or both). In this equation, *SWD* indicates if student *i* is a SWD in year t. θ_{st} is a school-year fixed effect and allows us to focus specifically on how SWDs and non-SWDs are being sorted within individual school-year combinations. The coefficient of interest, $\alpha_1^{subject,type}$, is interpreted as the difference in the probability a *SWD* has of being assigned to a teacher in the top quintile of the VAM distribution for a given type (SWD or non-SWD) and a given subject. *X* represents a vector of student characteristics and includes an indicator variable for the students race and free- or reduced-priced lunch eligibility.

Research Question 4: Are schools retaining teachers with higher VAM s?

Whether or not a student is assigned to a teacher in the top quintile of teacher effectiveness as measured by their VAM score for each subject and student type is, to some extent, determined by whether the district is able to retain such teachers. Following Equation (3), we measure how an increase in SWD and non-SWD VAMs relate to a teacher's probability of switching schools or leaving the district altogether. An important distinction about this analysis is that it does not determine the level of teacher attrition. Instead, we look to see if attrition differs across the distribution of VAM scores. Specifically, we compare the retention of higher VAM teacher to teachers with lower VAMs.

Results

RQ1: Do some teachers have a relative advantage in teaching SWDs over non-SWDs?

Figures 1a and 1b show the relationship between a teacher's SWD and non-SWD VAMs for math and ELA courses by plotting the difference between the two VAMs (DVAM) for all teachers. As previously explained, a negative DVAM indicates that the teacher falls into a higher percentile on the SWD VAM distribution than for their non-SWD VAM. These figures show that some teachers do exhibit a relative advantage in teaching SWDs over non-SWDs for both subjects. The y-axis represents the number of teachers that fall into each DVAM bin, and the bin width is set to 5. For example, in Figure 1a, teachers to the right of zero exhibit a relative advantage for SWDs in math courses. The further to the right of zero, the greater the magnitude of the teacher's DVAM which indicates a larger relative advantage towards SWDs. 57 teachers have a DVAM between -55 and -50,[8] and we would interpret these teachers has having a greater relative advantage with SWDs than the 156 teachers that fall into the -30 to -25 DVAM bin. While roughly symmetric, there is some skew in Figure 1a, indicating that slightly more teachers exhibit a relative advantage in teaching SWDs than non-SWDs. However, Figure 1b seems more symmetric which indicates that for ELA, the number of teachers with a relative advantage over one group of students is similar to the number of teachers with a relative advantage over the other group.

To determine the extent to which the derived DVAMs are driven by measurement error, we also compare the distributions of the DVAM with a randomized DVAM, represented by the red portion of the Figures 2a and 2b. Figure 2a clearly shows that the variance in the original DVAM is greater than the randomized DVAM. This indicates that some teachers exhibit a relative advantage in one group of students over the other in math, and that these differences are larger than what we would expect by chance. However, the variances in the derived and randomly generated ELA DVAM distributions appear quite similar, suggesting that perhaps the estimated relative advantage of teachers with SWDs relative to non-SWDs in ELA may be largely due to noise. As a further test, we apply the Kolmogorov-Smirnov test and find that the

[8] See Appendix for figures with bin labels.

two DVAMs are statistically different from their respective randomized DVAMs. However, the Kolmogorov-Smirnov method tests whether two distributions are *identical*. So, while the distributions in Figure 1b are not exactly equal, they subjectively appear similar enough that for ELA it is difficult to distinguish relative advantages/disadvantages from random variation.[9]

Research Question 2: Do teachers with higher SWD VAMs share the same observable characteristics as teachers with higher non-SWD VAMs?

Table 2 shows the results of Equation (3). Each cell represents a different regression with the outcome on the left-hand side. For example, regressing *% Time Certified* on SWD VAM surprisingly reveals that teachers with higher SWD VAMs were fully certified for a smaller proportion of their time in the district over the eleven-year sample. Column (2) indicates no statistically significant relationship between the proportion of time teachers were fully certified and having a higher non-SWD VAM. However, Column (3), which shows the p-value of the Wald test which compares if the coefficients across both equations are equivalent, suggests that the coefficients are not equal; the proportion of time teachers are certified matters for effectiveness with SWDs but not for non-SWDs. Specifically, the p-value of 0.000 in column (3) indicates that higher SWD VAM math teachers are statistically more likely to be fully certified for less time than higher non-SWD math teachers. Interestingly, this result is not consistent with ELA. In column (4), we see that being a top SWD teacher in ELA is associated with more time being fully certified, which is a similar result to top non-SWD ELA teachers.

[9] The Kolmogorov-Smirnov method tests whether two distributions are identical. Due to our large sample size, we reject the null that our DVAM distributions and randomized DVAM distributions are equal. However, as Figure 1b fails the "eye test", we plan to implement and include results of a Cucconi test in future versions of this paper.

For our sample, teachers with higher VAMs in math courses are more likely to be female while teachers with higher VAMs in ELA courses are more likely to be male. We find that higher math VAMs and higher ELA VAMs are associated with a higher likelihood of being Asian and White and a lower likelihood of being Black and Latino\a.

Higher SWD VAM teachers in math courses are more likely to be female than higher non-SWD VAM teachers as seen by Column (3). However, the opposite is true for ELA courses; teachers with higher SWD VAMs are more likely to be male than teachers with higher non-SWD VAMs. For math courses, teachers with higher SWD VAMs are less likely to be Black or Latino\a than teachers with higher non-SWD VAMs. For ELA courses, teachers with higher SWD VAMs are less likely to be Asian or Black than teachers with higher non-SWD VAMs.

Research Question 3: Do SWDs sort into classes taught by a teacher with high VAMs? If so, does it differ by disability type?

Table 3 indicates that SWDs are significantly less likely to be in classrooms led by teachers within the top SWD or non-SWD teachers across both subjects. Since the regressions include school-year fixed effects, these results indicate that SWDs are not being taught by the highest performing teachers *within* their schools. School-year fixed effects should help mitigate the effect being driven by other factors that influence teacher quality distribution between schools, such as the students' income levels (Papay, 2013).

While the relationships are statistically significant, the magnitudes themselves are fairly small. For instance, a SWD is one percentage point less likely to have a top SWD math teacher than a peer without disabilities. That said, the overall pattern of SWDs being less likely to be placed in classes taught by top teachers is consistent regardless of subject of type of VAM. However, there does seem to be a silver lining. Comparing Columns (1) and (2) seems to indicate that SWDs are sorting into math classes with top quintile SWD teachers, as well as classes taught by top quintile teachers in both groups (Column 3), at a higher rate than top quintile non-SWD teachers for math courses. This pattern also exists for ELA courses. While top quintile non-SWD teachers can still provide immeasurable value to SWDs, there is an argument to be made that SWDs would be better off being in a classroom led by a top quintile SWD teacher.

Table 4 also follows Equation (4) with the exception that *SWD* is now separated by variables which indicate disability type. As previously mentioned, students may have multiple disabilities which makes the disability types not mutually exclusive. Each coefficient under a disability category is compared to students without disabilities. The results from Table (3) seem to be mostly driven by the *SLD* disability type. This is unsurprising since this category represent 68.1% of SWDs. When controlling for race and free- or reduced-priced lunch eligibility, students categorized under *Autism* seem to be more likely to be enrolled in classrooms taught by top SWD teachers than any other disability type. This is seen by comparing Columns (1) & (2) and (4) & (5) across each row of disability type. For example, students categorized with *Autism* are 0.07 percentage points more likely than non-SWDs to be taught by top quintile SWD VAM math teachers which is greater than the -0.13 (*SLD*), -0.05 (*LSI*), and -0.08 (*Other Disability*) percentage points for the remaining disability categories. Even more so, students categorized under *Autism* are more (equally) likely to be enrolled in these classrooms than their non-SWD counterparts in math (ELA) courses. While we try to mitigate other factors that influence teacher quality distribution between schools by including school-year fixed effects, it should be noted that students categorized under *Autism* were, on average, 13 percentage points less eligible for free- or reduced-priced lunch than the overall student body and 15.9 percentage points lower than all SWDs.

Research Question 4: Are schools retaining teachers with higher VAM s?

A potential mechanism for why SWDs are less likely to be enrolled in classes taught by the most effective teachers (as measured by their VAMs) is that schools may not be able to retain the best teachers. Table 5 suggests that the most effective teachers –whether in math or ELA or for SWDs or non-SWDs -- do not leave LAUSD at a significantly higher rate than do other teachers. Moreover, in accordance with work by (Goldhaber, Gross, & Player, 2011) that shows that higher quality teachers are more likely to remain in their own schools, we find that an increase in VAMs is associated with a decrease in switching schools by about 1.3 percentage points. Also, the evidence presented here suggests that a one standard deviation increase in non-SWD math, SWD ELA, and non-SWD ELA VAMs are associated with a smaller proportion of time switching schools within the district over the eleven-year sample. Columns (3) & (6) present the p-values for the Wald test comparing the coefficients in the previous two columns. We find that teachers with higher SWD math VAMs are more likely to switch school than teachers with higher non-SWD math VAMs. While these results are not meant to be causal, they do provide suggestive evidence that schools in LAUSD may be less able to retain their most effective teachers of SWDs.

Discussion & Further Work

Students with disabilities can benefit from learning within general education classrooms. However, as more SWDs are introduced into these settings, it is unclear whether teachers are equally effective at teaching SWD compared to their peers without disabilities. Our results suggest that teachers who are effective overall are not synonymous with teachers who are best able to support SWDs. By plotting each teacher's DVAM (non-SWD VAM – SWD VAM), we find that a sizeable amount of the top performing teachers for non-SWDs are not necessarily the most effective teachers for SWDs (as measured by VAMs). This result especially holds for math courses while the ELA results are inconclusive. In future versions of the paper, we intend to test the robustness of our SWD and non-SWD VAMs by including testing accommodation data. Also, we would like to preform this analysis by disability type by restricting Equation (1) to students of a specific disability. Once each teacher has a VAM associated with a disability type, we intend to repeat the DVAM analysis to see if teachers exhibit a relative advantage in instructing specific disability types.

Preferably, principals would be able to identify which teachers will have a relative advantage in teaching specific student groups when making classroom assignments. Unfortunately, there does not seem to be any observable characteristics that distinguish which teachers will have a relative advantage in teaching SWDs. Of course, while not ideal, once a teacher's SWD and non-SWD VAM can be calculated, it would be possible for principals to determine each teacher's relative advantage and designate students accordingly.

We find that students with disabilities have less access to high VAM teachers. Specifically, students with disabilities have a lower probability of being taught by teachers in the top quintile of VAMs, regardless of if we are looking at SWD VAMs or non-SWD VAMS. While, these effects are relatively small, they are consistent across subjects and VAM type. .

A silver lining is that top teachers do not seem to be switching schools at a higher rate than teachers with lower VAM scores. In fact, we find that teachers with higher VAMs seem to switch schools at a lower rate than teachers with lower VAMs. However, when looking between top math VAM teachers, we also find that top SWD math teachers seem to leave at a higher rate than top non-SWD math teachers.

Ultimately, our study explores whether some teachers may have a relative advantage in teaching students with disabilities, a traditionally underserved group of students in general education classrooms. We find that while some teachers have both a relative and absolute advantage in teaching SWD, SWDs are less likely than their non-SWD counterparts to be placed in classrooms with top SWD VAM teachers. If principals were able to determine which general education teachers held the advantage for educating SWDs, they would be able to shift student-teacher matches accordingly. Then, there could be increases in SWD outcomes without overhauling the way teachers are trained.

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Tables & Figures

Table 1. *Student & Teacher Characteristics*

	SWD	Autism	SLD	LSI	Other Dis.	Test (ELA)	Test (Math)	FRL	ELL	Female	Asian	Black	Latino/a	White	Other Race
Student[1]	0.100	0.008	0.066	0.011	0.021	0.011	0.076	0.839	0.372	0.495	0.042	0.088	0.740	0.100	0.030
N = 698,458	(0.300)	(0.090)	(0.249)	(0.106)	(0.144)	(0.946)	(0.971)	(0.505)	(0.591)	(0.500)	(0.201)	(0.284)	(0.439)	(0.300)	(0.170)
Student-Year	0.086	0.007	0.059	0.008	0.017	0.023	0.073	0.798	0.318	0.496	0.040	0.073	0.758	0.099	0.031
N = 1,788,510	(0.281)	(0.084)	(0.235)	(0.088)	(0.130)	(0.965)	(0.999)	(0.401)	(0.466)	(0.500)	(0.195)	(0.260)	(0.428)	(0.299)	(0.173)
SWD	1.000	0.082	0.681	0.091	0.201	-0.722	-0.608	0.819	0.474	0.350	0.018	0.092	0.767	0.105	0.018
N = 152,513	(0.000)	(0.274)	(0.466)	(0.287)	(0.400)	(0.830)	(0.830)	(0.385)	(0.499)	(0.477)	(0.133)	(0.289)	(0.423)	(0.306)	(0.134)
Autism	1.000	1.000	0.056	0.017	0.048	-0.178	-0.082	0.660	0.270	0.145	0.064	0.078	0.579	0.235	0.044
N = 12,546	(0.000)	(0.000)	(0.230)	(0.131)	(0.213)	(0.973)	(1.013)	(0.474)	(0.444)	(0.352)	(0.245)	(0.268)	(0.494)	(0.424)	(0.206)
SLD	1.000	0.007	1.000	0.025	0.035	-0.895	-0.760	0.856	0.545	0.395	0.011	0.081	0.826	0.069	0.013
N = 104,281	(0.000)	(0.081)	(0.000)	(0.158)	(0.183)	(0.711)	(0.718)	(0.351)	(0.498)	(0.489)	(0.103)	(0.273)	(0.379)	(0.254)	(0.112)
LSI	1.000	0.016	0.191	1.000	0.052	-0.288	-0.153	0.818	0.422	0.261	0.029	0.083	0.764	0.102	0.021
N = 13,267	(0.000)	(0.124)	(0.393)	(0.000)	(0.222)	(0.949)	(0.961)	(0.386)	(0.494)	(0.439)	(0.169)	(0.276)	(0.425)	(0.303)	(0.144)
Other Disability	1.000	0.019	0.117	0.023	1.000	-0.544	-0.503	0.770	0.332	0.296	0.019	0.137	0.648	0.171	0.025
N = 30,448	(0.000)	(0.138)	(0.322)	(0.151)	(0.000)	(0.877)	(0.869)	(0.421)	(0.471)	(0.457)	(0.136)	(0.344)	(0.478)	(0.377)	(0.155)

	% Time Cert.	% Time SpEd Cred	% Time Master's	Ever Leave	% Time Swtich	Attend. Rate	Obs. Score	Hire Score	Years of Exp.	Female	Asian	Black	Latino/a	White	Other Race
Teacher	0.766	0.006	0.311	0.046	0.075	97.053	2.50	88.25	8.64	0.698	0.086	0.102	0.392	0.385	0.065
N = 6,300	(0.423)	(0.080)	(0.463)	(0.209)	(0.297)	(4.267)	(0.577)	(2.363)	(2.203)	(0.459)	(0.280)	(0.303)	(0.488)	(0.487)	(0.247)

[1] A student's status on a characteristic may change across years. The first row represents the percent of students that have ever been indicated with the repsective status. Remaining rows indicate student-year observations pooled across SY 2007-08 to SY 2017-18. *SWD* (student with disability). *SLD* (specific learning disability). *LSI* (language & speech impairment). *FRL* (free- or reduced-price lunch). *ELL* (English language learner). *Cert* (fully certified). *SpEd Cred* (special education accreditation). *Ever Leave* is an indicator for ever leaving LAUSD. *Switch* is an indicator for ever changing schools within LAUSD. *Obs. Score* is an observation score graded out of 4. *Hire Score* is out of 100. *Exp* (experience) is top coded at 10 years.

Table 2. *Teacher Observables on VAMs*

	Math VAM			ELA VAM		
	SWD	Non-SWD	(1) = (2) p-value	SWD	Non-SWD	(4) = (5) p-value
Regression Outcomes	(1)	(2)	(3)	(4)	(5)	(6)
% Time Certified	-0.018**	0.003	0.000	0.019**	0.012*	0.250
	(0.006)	(0.006)		(0.006)	(0.006)	
% Time Master's	0.000	-0.006	0.379	0.007	0.005	0.810
	(0.007)	(0.007)		(0.007)	(0.007)	
Attendance Rate	0.036	0.104	0.601	0.306	0.058	0.175
	(0.226)	(0.243)		(0.156)	(0.141)	
% Time SpEd Cred.	-0.001	-0.003*	0.180	0.001	-0.002	0.082
	(0.001)	(0.001)		(0.001)	(0.001)	
Female	0.211***	0.019**	0.000	-0.155***	-0.061***	0.000
	(0.006)	(0.007)		(0.006)	(0.006)	
Asian	0.017***	0.022***	0.244	0.003	0.017***	0.000
	(0.004)	(0.004)		(0.004)	(0.004)	
Black	-0.012**	-0.030***	0.000	-0.024***	-0.032***	0.061
	(0.004)	(0.004)		(0.004)	(0.004)	
Latino\a	-0.018*	-0.001	0.018	-0.022**	-0.032***	0.154
	(0.007)	(0.007)		(0.007)	(0.007)	
White	0.014**	0.011***	0.629	0.043**	0.047**	0.616
	(0.007)	(0.007)		(0.007)	(0.007)	
Other	0.003***	0.000***	0.504	0.005***	0.004***	0.641
	(0.004)	(0.004)		(0.003)	(0.003)	

Each row represents a separate regression with outcome variables on left-hand side. Columns (3) and (6) is the p-value associated with a Wald test between the coefficients in previous two columns. *p < 0.05, **p < 0.01, and ***p < 0.001. *VAM* (Value-Added Measure). *ELA* (English Language Arts). *SWD* (Student with Disability).

Table 3. *Top Quintile VAMs on SWD Status*

	Top Quintile Math VAM			Top Quintile ELA VAM		
	SWD (1)	Non-SWD (2)	Both (3)	SWD (4)	Non-SWD (5)	Both (6)
SWD	-0.010***	-0.022***	-0.010***	-0.020***	-0.028***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Asian	0.030***	0.029***	0.016***	0.033***	0.035***	0.031***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Black	-0.053***	-0.052***	-0.040***	-0.074***	-0.073***	-0.053***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Latino\a	-0.054***	-0.039***	-0.037***	-0.081***	-0.075***	-0.059***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Other	-0.027***	-0.018***	-0.021***	-0.031***	-0.040***	-0.029***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
FRL	-0.027***	-0.018***	-0.019***	-0.046***	-0.047***	-0.035***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	1,550,756	1,550,756	1,550,756	1,647,296	1,647,296	1,647,296

Observations span from SY 2007-08 to SY 2017-18. All regressions include a school-year fixed effect. Student-level clustered standard errors in parentheses. *p < 0.05, **p < 0.01, and ***p < 0.001. *VAM* (Value-Added Measure). Each column represents an indicator for a teacher being in the top quintile for the type and subject of each VAM. *Top Quintile* refers to the top quintile of each respective group *VAM*. *ELA* (English Language Arts). *SWD* (Student with Disability). *FRL* (Free- or Reduced-priced Lunch). White is used as the base for student race and *Other* subsumes races not within the above categories.

Table 4. *Top Quintile VAMs on Disability Type*

	Top Quintile Math VAM			Top Quintile ELA VAM		
	SWD (1)	Non-SWD (2)	Both (3)	SWD (4)	Non-SWD (5)	Both (6)
Autism	0.007*	-0.007*	0.001	0.000	-0.017***	-0.007**
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
SLD	-0.013***	-0.023***	-0.011***	-0.025***	-0.030***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LSI	-0.005	-0.010***	-0.003	-0.007*	-0.004	-0.004
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Other Disability	-0.008***	-0.019***	-0.009***	-0.010***	-0.021***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Asian	0.030***	0.029***	0.016***	0.033***	0.035***	0.032***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Black	-0.053***	-0.052***	-0.040***	-0.073***	-0.072***	-0.053***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Latin\a	-0.054***	-0.039***	-0.037***	-0.081***	-0.075***	-0.059***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Other	-0.026***	-0.018***	-0.021***	-0.030***	-0.040***	-0.029***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
FRL	-0.027***	-0.018***	-0.018***	-0.046***	-0.047***	-0.035***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	1,550,756	1,550,756	1,550,756	1,647,296	1,647,296	1,647,296

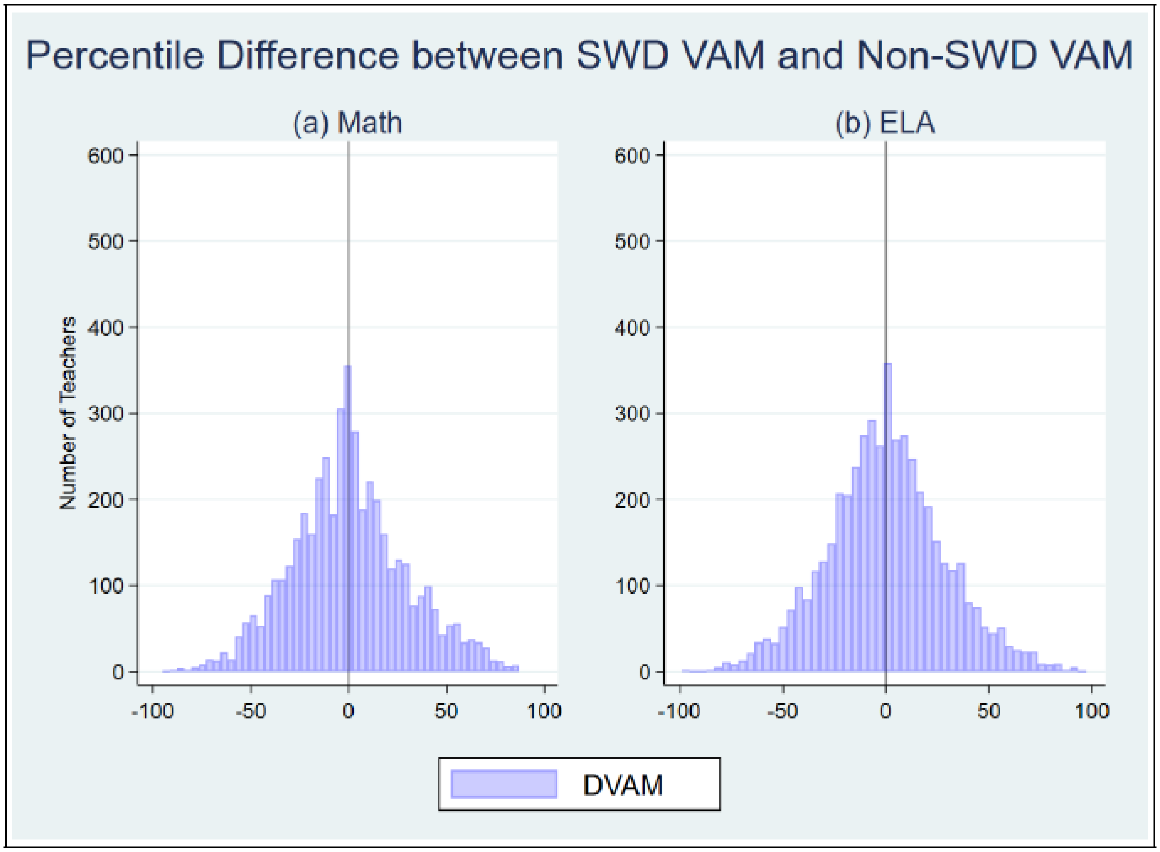
Observations span from SY 2007-08 to SY 2017-18. All regressions include a school-year fixed effect. Student-level clustered standard errors in parentheses. *p < 0.05, **p < 0.01, and ***p < 0.001. Each column represents an indicator for a teacher being in the top quintile for the type and subject of each VAM. *Top Quintile* refers to the top quintile of each respective group *VAM*. *VAM* (Value-Added Measure). *VAM*. *ELA* (English Language Arts). *SWD* (Student with Disability). *SLD* (Specific Learning Disability). *LSI* (Language Speech Impairment). *FRL* (Free- or Reduced-priced Lunch). White is used as the base for student race and *Other* subsumes races not within the above categories.

Table 5. *Teacher Retention on VAMs*

	Math VAM			ELA VAM		
	SWD	Non-SWD	(1) = (2) p-value	SWD	Non-SWD	(4) = (5) p-value
Regression Outcomes	(1)	(2)	(3)	(4)	(5)	(6)
Ever Leave District	-0.003	-0.003	0.927	-0.004	-0.001	0.312
	(0.003)	(0.003)		(0.002)	(0.002)	
% Time Switch Schools	-0.003	-0.013***	0.005	-0.014***	-0.015***	0.757
	(0.004)	(0.004)		(0.004)	(0.004)	

Each row represents a separate regression with outcome variables on left-hand side. Columns (3) and (6) is the p-value associated with a Wald test between the coefficients in previous two columns. *p < 0.05, **p < 0.01, and ***p < 0.001. *VAM* (Value-Added Measure). *ELA* (English Language Arts). *SWD* (Student with Disability).

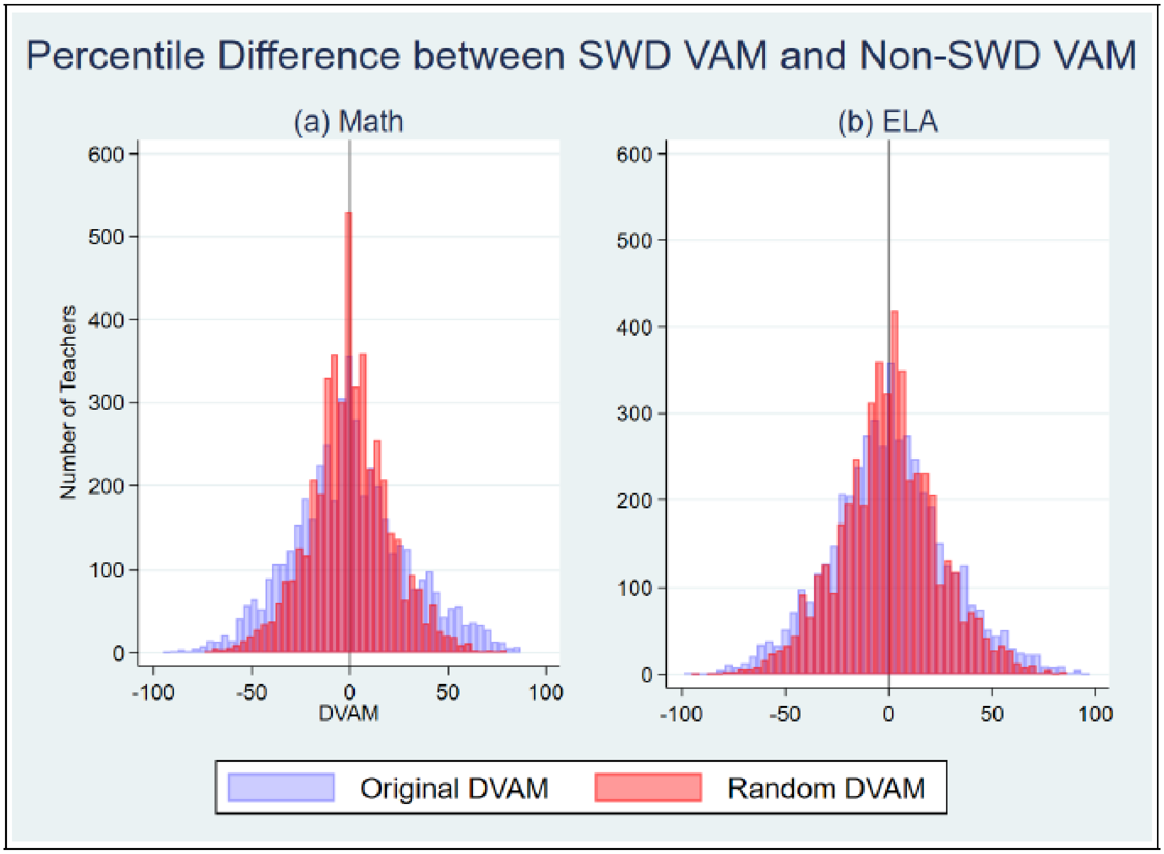
Figure 1



DVAM is the difference between Non-SWD and SWD VAMs ((Non-SWD VAM) - (SWD VAM)). *VAM* (Value-Added Measure). *ELA* (English Language Arts).

2/12/2021

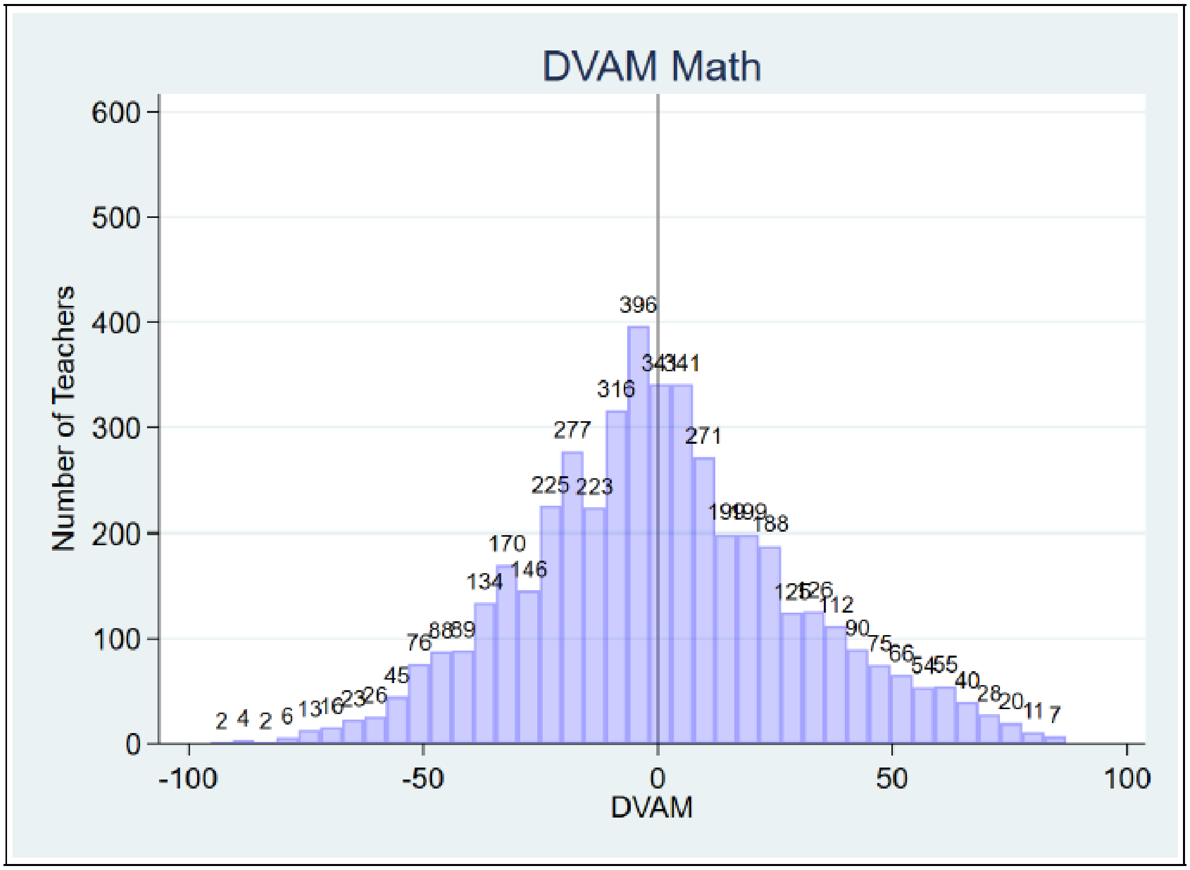
Figure 2



DVAM is the difference between Non-SWD and SWD VAMs ((Non-SWD VAM) - (SWD VAM)). *VAM* (Value-Added Measure).

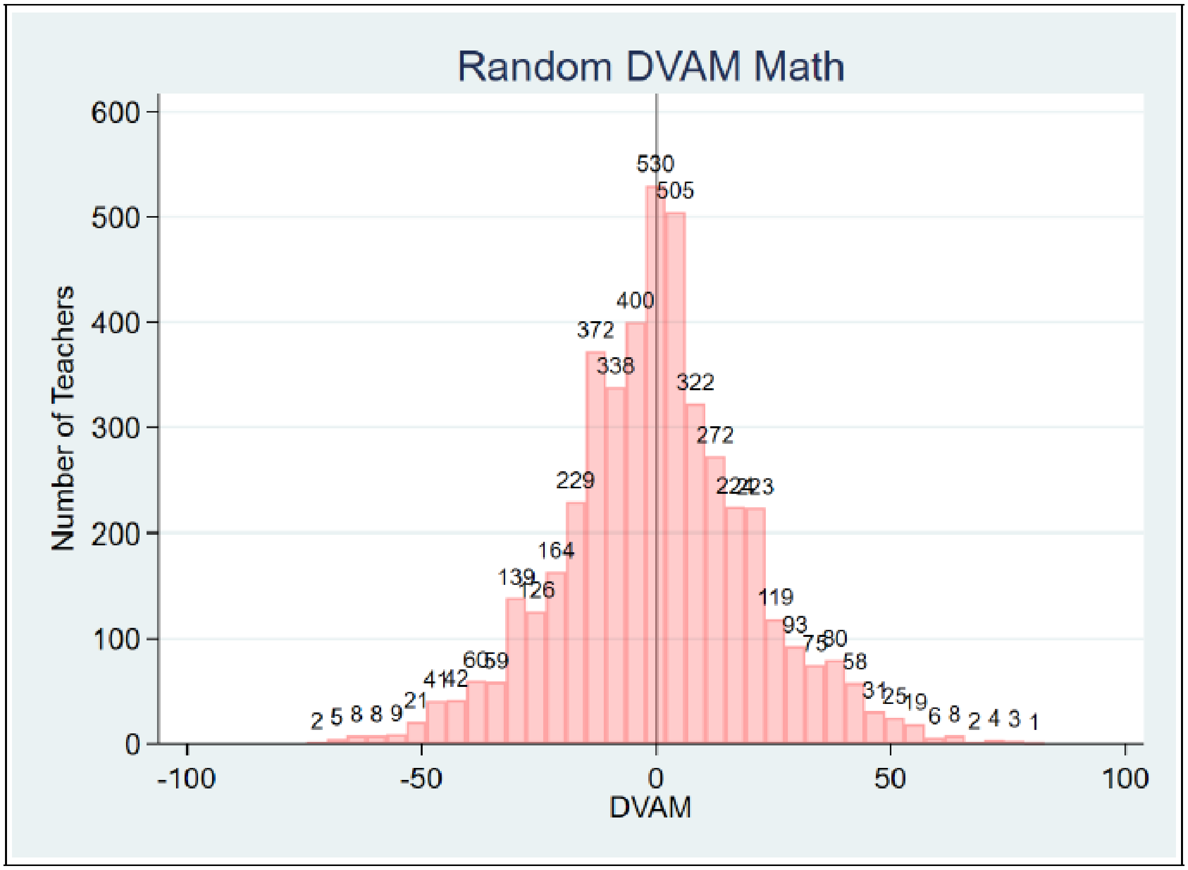
Appendix

Figure 3



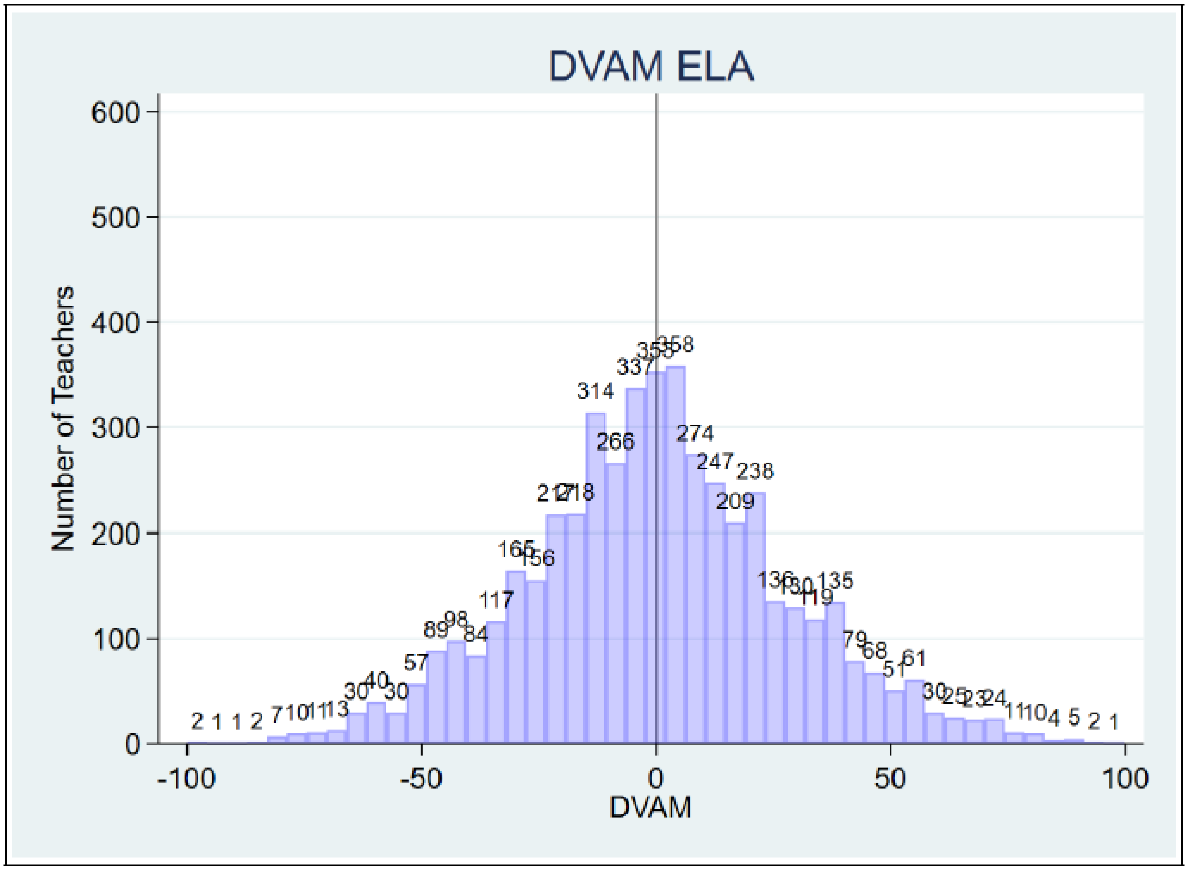
DVAM is the difference between Non-SWD and SWD VAMs ((Non-SWD VAM) - (SWD VAM)). *VAM* (Value-Added Measure).

Figure 4



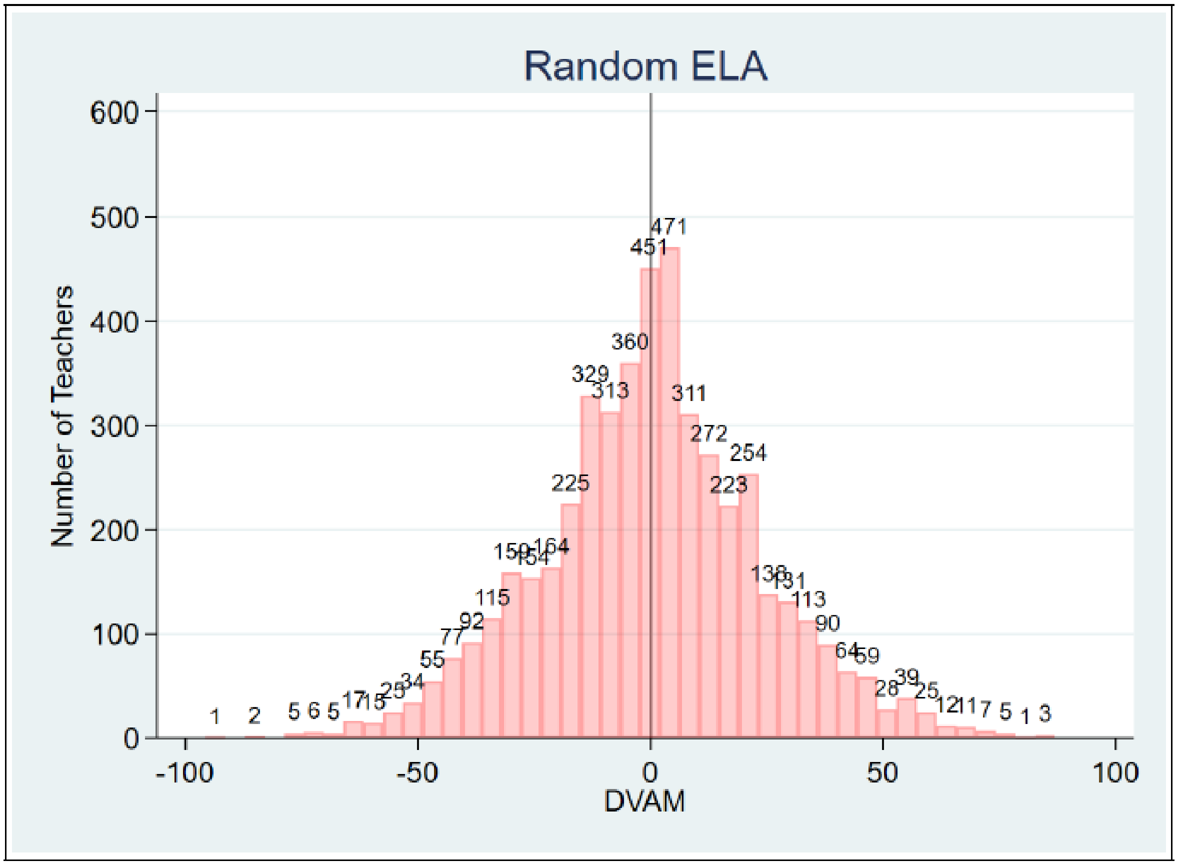
DVAM is the difference between Non-SWD and SWD VAMs ((Non-SWD VAM) - (SWD VAM)). *VAM* (Value-Added Measure).

Figure 5



DVAM is the difference between Non-SWD and SWD VAMs ((Non-SWD VAM) - (SWD VAM)). *VAM* (Value-Added Measure).

Figure 6



DVAM is the difference between Non-SWD and SWD VAMs ((Non-SWD VAM) - (SWD VAM)). *VAM* (Value-Added Measure). *SLD* (Specific Learning Disability). *LSI* (Language/Speech Impairment). *Rand.* (Randomized).