Do Flexible Funding Models Increase Rates of Special Education Identification?

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Abstract

This study builds on existing research on the potential impact of different state funding policies on the observed variation in special education identification rates nationwide. Using publicly available data from the U.S. Department of Education from 2005 to 2017, I employ a difference-in-differences strategy to isolate the potential causal impact of a change in Nevada state policy from a census-based funding model to a formula-based funding model in 2016 by comparing Nevada to its unchanged neighboring state, California. I find no significant differences in the identification rates of children with special needs in Nevada following the state's policy change. Results are consistent across student age ranges, genders, English language learner status, and all major racial and ethnic subgroups.

I. Introduction

Public schools in the United States are obligated by federal law to find and identify students with unidentified disabilities and to provide them with special education and related services (IDEA 2004). State education agencies, under the Individuals with Disabilities Education Act (IDEA), are thereby required to ensure that children suspected of having an undiagnosed disability are referred for formal evaluation, the results of which determine the specialized services a child will receive, as well as the level of funding a school will receive to support the student based on their classification. This level of funding varies across states, as a result of differing funding structures and definitions of disabilities (McCann 2014; Müller 2005).

Most disabilities with a clear medical basis are diagnosed by a child's parents or doctor in their preschool years (Reschly 1996). The students identified and evaluated by schools based on academic or behavioral performance issues, however, account for the majority of the 6.6 million students with disabilities in the U.S. (Reschly 1996; U.S. Department of Education). Among the federally-defined categories of disabilities, there is an informal distinction between those for which student qualification is clear-cut (e.g., deafness, blindness) and those categories for which student qualification is highly sensitive to human pressure and interpretation (e.g., specific learning disability, intellectual disability, emotional disturbance) (Sullivan and Bal 2013; Schifter et al. 2019). Recent research has highlighted significant inconsistencies by race and socioeconomic status in the identification rates of children with these types of exceptionalities, in particular, lending further support to the notion that student identification for these disability categories is subjective and affected by human influence (Dhuey and Lipscomb 2011; Shifrer, Muller, and Callahan 2011; Morgan et al. 2017; Schifter et al. 2019).

The proportion of students identified for special education varies significantly across states—from 8.6 percent of all public-school students in Texas compared to 17.8 percent of all public-school students in New York (U.S. Department of Education). Nationwide, the average rests around 13 percent of all public-school students (U.S. Department of Education). The range in proportions of students with special needs across states—when, in theory, a child's state of residence should have no consistent impact on the likelihood of their having an academic or behavioral disability—has led researchers and policymakers to wonder whether state funding structures are affecting the identification rates of students for special education. If true, upticks in identification rates of students with disabilities would most likely be seen in the subjective disability categories.

Prior literature has assessed alternate hypotheses driving this observed variation in state rates of special education identification and has resulted in a variety of conclusions. Some evidence points to the influence of standardized testing on increased identification rates (Figlio 2002). Other studies have found that the misidentification of English language learners as having special needs may play a role in identification rate variation across states, given the non-randomness of English language learner residency within the U.S. (Sullivan 2011). Researchers have also assessed the impact of a child's entering school at a younger age than the rest of their peer cohort on their likelihood of being diagnosed as having special needs (Dhuey and Lipscomb 2010). The bulk of extant economic literature, however, has examined the role of fiscal incentives on identification rates, likely due to the ease with which comparisons can be drawn between states by this policy measure. Despite researchers' focus on this potential causal mechanism, the findings to date have been mixed about the role of funding structures in affecting rates of special education identification, signaling a need for additional research.

This paper will exploit a change in funding structures for one state, Nevada, compared to an unchanged neighboring state, California, in an attempt to isolate the potential influence of state funding mechanisms on rates of disability identification. I use publicly available data from the U.S. Department of Education on the number of students identified within each state for special education annually from 2005 to 2017. I employ a difference-in-differences methodology—an identification strategy which allows for the isolation of any potential causal impact of the change in Nevada state policy by using the constancy of California's state funding policies as a counterfactual. While many states in the past decade have made small adjustments to their funding policies for special education, Nevada is the most recent state to adjust its funding for special education in such a significant way (e.g., from one funding model to another, rather than smaller changes to the percentage of state funds allotted to special education). This type of policy change is a unique opportunity to analyze of the impact of changing from a census-based funding model, in which state funds are allocated for special education regardless of the number of students with special needs, to the more flexible, formula-funded model used by two-thirds of states in the U.S., which allocates funds based on the number of students identified for special services annually. Further, California is one of the few states to have made no adjustments to its funding model for special education in the time period considered in this study (ECS 2015), bolstering its methodological appeal as a comparison group.

The remainder of this paper is organized as follows. In Section II, I begin with a brief background on the processes of special education identification in California and Nevada, as well as provide context for the two special education funding models under consideration in this paper. Section III describes the extant literature on special education identification rates and the potential influence of different funding models. Section IV details the dataset and methodology used in this paper, and Section V provides the results of my estimation of the impact of fiscal incentives on disability identification rates. Section VI concludes the paper with a discussion of the implications of my findings.

II. Background

Processes for Identifying Students with Special Needs

The Individuals with Disabilities Act covers 13 disability categories: specific learning disability, other health impairment, autism, emotional disturbance, speech or language impairment, visual impairment, deafness, hearing impairment, deaf-blindness, orthopedic impairment, intellectual disability, traumatic brain injury, and multiple disabilities (IDEA 2004). The responsibility for identifying and evaluating children who may have a disability rests with state and local education agencies, in a process that IDEA calls “child find” (IDEA 2004). The “child find” provision of the law mandates that all public schools evaluate students demonstrating potential signs of disabilities. For students who attend public schools and who are not referred for special education through an external medical professional, there is a formalized referral process for special education services. States may vary slightly in the specifics of this process, but the timelines schools are bound by for each stage of the referral and evaluation processes are standardized by federal law (e.g., schools have no more than 60 days after a parent’s informed consent to convene an initial individualized education program [IEP] meeting for an identified student). See Figure 1 and Figure 2 for diagrams of what this process looks like for California and Nevada, respectively, noting that there are no significant differences in identification processes between the two states.

While states must all follow IDEA regulations in terms of providing services for students diagnosed with any of the 13 disability categories covered for special education services, they may independently define who qualifies for each disability type. However, a study from 2005 analyzing variation in state disability definitions found no statistically significant differences in the proportion of students served within each federal disability category as a result of cross-state variation in eligibility criteria (Müller 2005). As such, I do not expect any differences in either the processes of special education referral and identification or the definitions of disability categories across the two states considered in this study to bias the findings.

State Special Education Funding Models

Increasingly large shares of elementary and secondary education spending in the U.S. have been devoted to special education in recent decades, as a result of the continued rise in the number of students identified for specialized school services (Hanushek and Rivkin 1997; Alonso and Rothstein 2010; Mahitvanichcha and Parrish 2005). The goal of this paper is to better understand the role of fiscal incentives affecting special education identification, as a potential explanation of the variation observed in identification levels across states.

While there is some wider variation in the specific design of state funding formulas for special education, there are essentially two main forms: census- or population-based funding and formula-funding models. Census-based funding models allocate money from a fixed annual amount based on the total number of children enrolled in a district, regardless of the number of special education students. This more rigid funding structure is currently used by six states (ECS 2015; McCann 2014).

The more common funding structure is that of a formula-funding model where money is allocated within a state with consideration to the provision of special education and its related costs. These funding structures vary but can include weights for special education students based on their disability or intensity of services needed, district-level reimbursements for a certain percentage of special education expenditures, flat grants at a fixed amount based on the number of identified special education students, or funding based on the calculated resource needs of students (i.e., teachers or classroom space) for specific disability types (McCann 2014; Mahitvanichcha and Parrish 2005; Reschly 1996).

This paper will focus on a comparison of these two broad funding structures with an eye toward the potential consequences of using the more common, flexible-funding policy. Both funding structures make it simple to predict how a change in the number of identified students with disabilities would affect the amount of money a district or school would receive. States using formula-funding structures would theoretically incentivize the *over*-identification of students with disabilities—particularly students identified within subjective disability categories, while census-based structures would theoretically lead to the *under*-identification of students with disabilities, given a state's incentive to reduce overall costs relative to the size of its population. Notable for the purposes of this paper is that Nevada, which switched from a census-based funding structure to a formula-funding model in 2015, applies a common weight to *all* students with disabilities of 2.0 (Nevada Legislative Counsel Bureau 2017). This common weighting scheme lends further credence to the hypothesis that if the formula-funding structure does lead to higher rates of special education identification, that impact is most likely to be seen in the identification rates of subjective disability categories.

III. Previous Literature

Impact of Special Education Funding Structures

Over the past 20 years, as the scale of both special education identification and overall education spending have continued to rise, a handful of studies have explicitly examined the relationship between fiscal incentives and special education identification. Some studies have assessed the impact of school finance policy changes within single states, along the same lines as this paper, while others have taken a nationwide approach. A handful of studies have assessed fiscal policy impacts on identification rates while others have narrowed their focus to the effects on student placement decisions—decisions about where students spend time during the school day (i.e., primarily in a general education classroom, or removed to a secluded classroom). Results among all of these studies have been mixed, suggesting more research is needed.

Cullen (2003) used a difference-in-differences approach to exploit a change in Texas school finance policy to a more flexible funding model and found that the incentive system it created explained as much as 35 percent of the increase in student disability identification in the late 1990s. Similarly, Parrish (2000) examined the change in New York's special education financing based on reforms implemented in 1998 when the state considered a change to a census-based model but instead selected a funding structure including student weights based on the student's placement. Parrish determined that the new system's incentives for the inclusion of special education students within general education classroom settings, rather than seclusion or removal, did indeed result in more children with special needs spending the majority of their school day in general education environments. Finally, among single-state analyses, Dempsey and Fuchs (1993) assessed longitudinal data in Tennessee from the late 1970s to mid-1980s in terms of student placement decisions and found the change from a "flat" funding rate to a weighted formula was associated with a significant increase in more restrictive (and presumably more expensive) school placements for students with special needs.

Greene and Forster (2002) analyze state funding models for special education nationwide. They use a simple linear regression controlling for type of funding structure and conclude that non-census-based systems were associated with a significant increase in special education enrollment over a ten-year period (2002). However, Mahitivanichcha and Parrish (2004) attempted to replicate Greene and Forster's findings using the same data and found that the results were statistically insignificant. Mahitivanichcha and Parrish (2005) conducted a meta-analysis of empirical evidence as well as contextual evidence on state funding formulas and concluded the relationship between funding and special education identification to be complex and context-dependent, suggesting a need for additional, state-specific analyses.

The most recent analysis on this topic comes from Dhuey and Lipscomb (2011), who look at what they call "capitation" reforms, or state shifts to census-based funding models, and find that disability rates tend to fall—in line with theoretical expectations—as a result of this funding structure, especially in subjectively diagnosed categories. This paper will contribute to the extant literature by offering an examination of a recent shift in state policy for one state, Nevada, whose legislature voted to change from a census-based funding model to a formula-funding model in 2015. The focus on Nevada is relevant not just because of the recency of this policy change, but because the state's shift to a more flexible funding model allows for an analysis of the potential causal impact of this particular funding structure, which is currently in use by 32 other states (ECS 2015). Therefore, the findings of this study could have broader, nationwide implications.

The recent shift in Nevada policy is further evidence that the question of how to balance the appropriate level of support for students with special needs with state budget constraints is still a highly relevant policy question. Indeed, in 2016, the Vermont General Assembly commissioned a study in response to legislator concerns about high and continually increasing state spending levels for special education. The researchers concluded that state spending could be cut significantly if Vermont shifted to a census-based funding model from its reimbursement-based policy, with the caveat that a decrease in support available for special education students would likely have a significant impact on those students' school experiences (Kolbe and Killeen 2016).

Factors Predicting Likelihood of Disability

The analysis in this paper is predicated on an ability to isolate the impact of funding structures on disability identification rates, removing all other potentially confounding differences between California and Nevada that might be influencing this outcome of interest. There is a lack of definitive knowledge about individual factors known to be determinative of developing a disability during a child's school-age years. However, research has shown that there are some risk factors associated with the development of a learning disability, including having a parent with a learning disability, drug or alcohol use on the part of the parent while the child is in the womb, poor nutrition, and exposure to lead in water or paint (Cortiella and Horowitz 2014; Centers for Disease Control and Prevention 2013; Vogler, DeFries, and Decker 1985). While local variation in these metrics undoubtedly exists, there is no evidence to suggest that any of these factors are consistently and predictably correlated with the state in which a family resides. This means the influence of any one of these factors would generate the same amount of bias in the identification rates of students with disabilities for both states under consideration and would therefore be accounted for by the the difference-in-differences approach employed in this paper.

Outside of potential developmental factors influencing disability rates, literature in the past decade has explored the potential impact of high-stakes testing (Figlio 2002), the conflation of special needs with the needs of English language learners (Sullivan 2011), racial and gendered biases leading to the disproportionate identification of African-American boys (Artiles et al. 2010) and the under-identification of girls (Oswald et al. 2010), the age at which a child enters school (Dhuey and Lipscomb 2010), and the relationship between low-income households and identification rates (Sullivan and Bal 2013)—the last of which is likely highly correlated with many of the environmental factors impacting child development mentioned previously. Given this array of potential confounding factors, some of which may vary consistently by state and could therefore potentially bias this study's findings, I control for as many of these factors as possible given the data available.

IV. Data and Methodology

Data

This paper uses publicly available data from the U.S. Department of Education.[1] States are required to report special education student counts by age, race, gender, English language

[1] Three types of federal data were retrieved from the Department's Special Education Program, under the category of *IDEA* Section 618 Data Products: State Level Data Files. The data collections retrieved include Child Count and Exiting data, both authorized under *IDEA*, Section 618 Part B. Data were also retrieved from the National Center for Education Statistics within the Institute of Education Sciences, which collects annual data on total public-school student enrollment, and from Ed Data Express at ED.gov, which collects the total number of English Learners in each state on an annual basis – both of which were required for this analysis.

learner status, and disability type to the federal government on an annual basis.[2] Data are available from SY 2005-06 through SY 2017-18, allowing for 11 years of pre-policy analysis and two years of post-policy analysis for both California and Nevada. Two years of data following this policy change may not be enough to demonstrate the policy's causal impact on the change in long-term identification trends, but if there is a causal impact of this policy there should be an observable shift in identification rates within the first two years of implementation. Table 1 below provides summary statistics for California and Nevada for the years available.

Empirical Strategy

This paper examines the impact of one state's recent change in funding structure on its rates of special education identification. In June 2015, the Nevada state legislature voted to replace its census-based school funding model with a formula model, including a weight of 2.0 (two times the state per pupil expenditure) for all special education students (Nevada State Assembly 2015). This change was considered effective as of the 2016-17 school year (Nevada State Assembly 2016). Using a difference-in-differences strategy, I assess the impact of this shift in Nevada state policy by comparing Nevada to its neighbor, California, which used (and continues to use as of the writing of this paper) a census-based funding structure both before and after the enactment of the change in Nevada's policy in 2016 (Hill et. al. 2016). I estimate the following model:

$$Y_{st} = \propto + \beta State_s + \gamma Post_t + \lambda State_s * Post_t + \rho \boldsymbol{X}_{st} + \varepsilon_{st}$$

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[2] Disaggregation including the racial/ethnic categories of "Native Hawaiian/Other Pacific Islander" and "Two or More Races" began in 2008. Disaggregation by gender and English language learner status began in 2012.

where Y_{st} is the outcome of interest for state s in period t, measured as the proportion of students with disabilities identified out of the total public-school student population. $State_s$ is a dummy representing either Nevada or California, and $Post_t$ is a dummy indicating the period before or after 2016.[3] The coefficient λ indicates the causal effect of interest, and the vector $\boldsymbol{X}_{st}$ includes additional controls for student demographics including the number of students of each major race/ethnicity category, the number of female versus male students, the number of English language learners[4], and the number of students qualifying for free or reduced-price lunch. Given the literature on potential demographic factors influencing identification rates, each of these controls will contribute to minimizing potential omitted variable bias as a result of factors that may vary between the two states.

The assumption beneath this broader identification strategy is that Nevada and California, with similarly rigid funding formulas prior to 2016, had special education identification rates along parallel trends prior to Nevada's policy change. If the change in funding structure in Nevada had a marked impact on the state's rate of special education identification, there would be a distinct break point in those trend lines for Nevada beginning in SY 2016-17, while California continued along its same, pre-policy trend. The impact of the policy can be measured, then, in the difference between Nevada and California's special education identification rates before and after 2016. This strategy is superior to simply comparing Nevada's rates of enrollment to itself before and after the policy change, which would fail to control for the influence of any omitted variables in the region at the same time as the policy change. By

[3] The school years 2016-17 and 2017-18 are included in the post-policy period, while the years 2005-06 through 2015-16 make up the pre-policy period.
[4] Data on the number of English language learners within each state was collected by the U.S. Department of Education beginning in SY 2007-08, so there are two years of analysis for which this control is not available in the pre-policy period.

including California as an additional control, any bias caused by variables common to both states will be implicitly controlled for, even those variables unobserved.

Figure 3 demonstrates these parallel trends in the pre-period and the break in trends beginning in 2016. With the exception of the first two years of pre-policy data (2005 and 2006), California and Nevada appear to move along parallel trends in terms of special education identification rates for students ages 3 to 21 in the nine other years prior to 2016. There is a notable drop in identification rates for both states in 2010, for example, suggesting the influence of an environmental shock common to both states at that time. However, beginning in 2016, both states continue see increases in special education identification rates—with California even outpacing Nevada in terms of the proportion of special education students relative to the broader public-school student population, contrary to expectations.

Among the 13 disability categories represented in this dataset, I've coded the following five disabilities as "subjective" based on extant literature: emotional disturbance, intellectual disability, other health impairment, specific learning disability, and speech language impairment (Dhuey and Lipscomb 2011; Shifrer, Muller, and Callahan 2011; Morgan et al. 2017; Schifter et al. 2019). When limiting the analysis to the identification rates for this subset of disabilities, the trend lines look quite different (see Figure 4). For this subset of disabilities, parallel trends are not evident in the pre-period until 2009, and state identification rates appear to continue on parallel tracks even after the policy change's implementation in 2016. Figures 3 and 4 are the first indications that the "shock" of the funding policy shift in Nevada in 2016 may not have had any significant impact on special education identification rates in the state. Figures 5 and 6 show the trends in identification rates for each individual subjective disability for California and

Nevada, respectively. No significant differences in the rates of identification for any individual disability between the two states are evident before or after 2016.

In addition to the main regression detailed above, which assesses changes in special education identification rates among all public-school students ages 3 to 21, I employ the same difference-in-differences methodology to compare changes in identification rates for different types of disabilities (subjective and non-subjective), age ranges (early childhood, defined as ages 3 to 5, and elementary and secondary, defined as ages 6 to 21), all major racial and ethnic groups, both genders, and English language learner status to assess any potential differential impact for these subgroups as a result of the policy change.

V. Results

Findings

Tables 2 and 3 below display the results of a series of difference-in-differences analyses. Table 2 presents findings from regressions where the outcome variables of interest first vary the age range of students considered (ages 3 to 5, 6 to 21, and 3 to 21, represented in columns [1], [2], and [3], respectively) to compare the potential differential impact on identification rates for students in early childhood settings, in elementary or secondary school, and rates across the spectrum of public-school students covered by IDEA. Results are insignificant for the outcome variable limited to only children in early childhood settings (ages 3 to 5) but suggest that when looking at children across early childhood and elementary and secondary education settings, Nevada experienced a statistically significant, though small, *decrease* in the number of students identified for special education after the policy change in 2016—contrary to theoretical expectations. Model (3) shows Nevada experienced approximately a 0.005% decrease in special education enrollment for all students aged 3 to 21 as a result of the policy change ($p<0.10$). However, when demographic controls are added in models (4), (5), and (6), the results from all three regressions lose their statistical significance.

I hypothesized that if the Nevada policy change had any impact on special education identification rates, it would be seen most readily in the subjective disability categories, given that identification for these disabilities is most subject to human pressures and therefore most likely to be responsive to the presence of an external incentive (in this case, the financial incentive of increased funding for additional special education students). However, in models (7), (8), and (9), where the outcome variable is limited to just those disabilities considered subjective, and again broken down by age ranges 3 to 5, 6 to 21, and 3 to 21, there remains minimal evidence of any impact of the change in Nevada state policy in line with theoretical expectations. Models (8) and (9), assessing the impact of the policy on children ages 6 to 21 and 3 to 21, respectively, are again statistically significant and show a decrease for Nevada identification rates. However, the magnitude of the post-policy change has decreased even further compared to models (2) and (3), where all disabilities were considered, to approximately 0.0003% fewer students identified for special education ($p<0.05$), where an increase would be expected if the policy had the effect on identification rates expected. However, this finding is not statistically significantly different from zero, or the equivalent of no post-policy impact.

In Table 3, I further disaggregate special education identification rate outcomes by race, gender, and English language learner status, to compare potential differential impacts of the policy on these subgroups. I find statistically significant decreases in identification rates after 2016 for Asian and White students, and statistically significant increases in identification rates for Black and Native Hawaiian/Pacific Islander students. These findings, as well as those for the remaining racial and ethnic subgroups, are represented in columns (10) through (16) of the table. I find the change in funding policy had no impact on special education identification rates by gender, shown in the results from models (17) and (18) but did result in a statistically significant increase in ELL student identification, at a rate 0.004% higher following the 2016 policy change than in the years prior ($p<0.10$). Overall, while some of these findings are *statistically* significant, the magnitude of each is quite small, suggesting there may be no *substantive* significance to any of these results.

Limitations

This proposed strategy has several weaknesses. First, there are only two years of post-trend data publicly available. If there is a causal impact of Nevada's new funding policy, there should be an observable change within the first year or two of its implementation, but it is plausible that its long-term impacts may not be evident for several more years. The identification of students for special education is a slow process, and substantively significant shifts in identification rates could take more years to develop than there are currently years of publicly available data. That said, the preliminary evidence presented in this paper does not suggest any immediate impact of the shift in Nevada's special education funding policy on overall identification rates.

Additionally, this method of causal analysis assumes no other major changes occurred in Nevada or California at the same time as the shift in state funding policy that would also have impacted the rate of special education identification in the state. I conducted additional research to assess whether there were any additional shocks to the environment at the time that would impact my causal estimates (e.g., significant numbers of school closures, environmental concerns that resulted in a large reduction in the number of school days) and found no indications of environmental shocks in either state at the same time as the policy change. This research was by no means exhaustive; however, given the lack of impact seen after 2016, any underlying environmental shock would simply be contributing to the continuation of identification rate trends in Nevada even prior to 2016.

Finally, to assess the true potential impact of this policy on special education identification rates (and the underlying behaviors of school-based personnel who are making the student referrals), more robust data would be very useful. Data at the district or school level, including the number of referrals made in addition to the number of students found to have a disability, would enable a more thorough analysis of whether flexible-funding structures are having a direct causal impact on the identification rates of students with special needs, particularly for subjective disability categories. Data on individual student academic and behavioral data to compare with these referral rates would further enable a better analysis of this relationship, since other literature on this subject suggests there is likely a great deal of local variation in terms of the identification of students with special needs (Dhuey and Lipscomb 2011; Morgan et al. 2017; Schifter et al. 2019).

VI. Conclusion

The results of this study suggest that Nevada's shift to from a census-based model to a formula-funding model in 2016, with twice as much funding provided at the state level for special education relative to general education students, had no immediate impact on special education identification rates in the state. While some findings from the difference-in-differences strategy employed in this paper are statistically significant, the magnitude of those findings—

none larger than a 0.005% change in identification rates—casts doubt on their substantive significance and does not lend itself to immediate conclusions about the broader influence of formula-funding models. The methodological design of this study has accounted for sources of bias common to both California and Nevada during the period under consideration, and additional model controls for the student and household demographics account for other potential sources of bias that extant literature suggests may have an impact on identification rates. Given these controls, and the small magnitude of this study's findings, no immediate policy implications or conclusions can or should be drawn.

Future research on this subject should seek access to district- or school-level data, given the potential for differential impacts of a statewide funding policy change at the local level. Further, there is a chance that some other underlying and unaccounted-for characteristic of Nevada prevented this policy from impacting identification rates that may not be present in other states currently using formula-funding models. As such, more research on the differential impacts of this policy in a variety of state contexts is needed to help discern the policy's impact and whether or how it is one of the factors contributing to the observed variation in state special education identification rates.

Finally, previous literature suggests that standardized testing can play a role in affecting special education identification rates—a variable that was not accounted for in the present study. However, the common drop in identification rates seen in 2010 for both California and Nevada, in line with the onset of federal policy nudges via Race to the Top competitive grants, suggests that the potential influence of accountability and testing policies and their intersection with fiscal incentives may also be worth further exploration.

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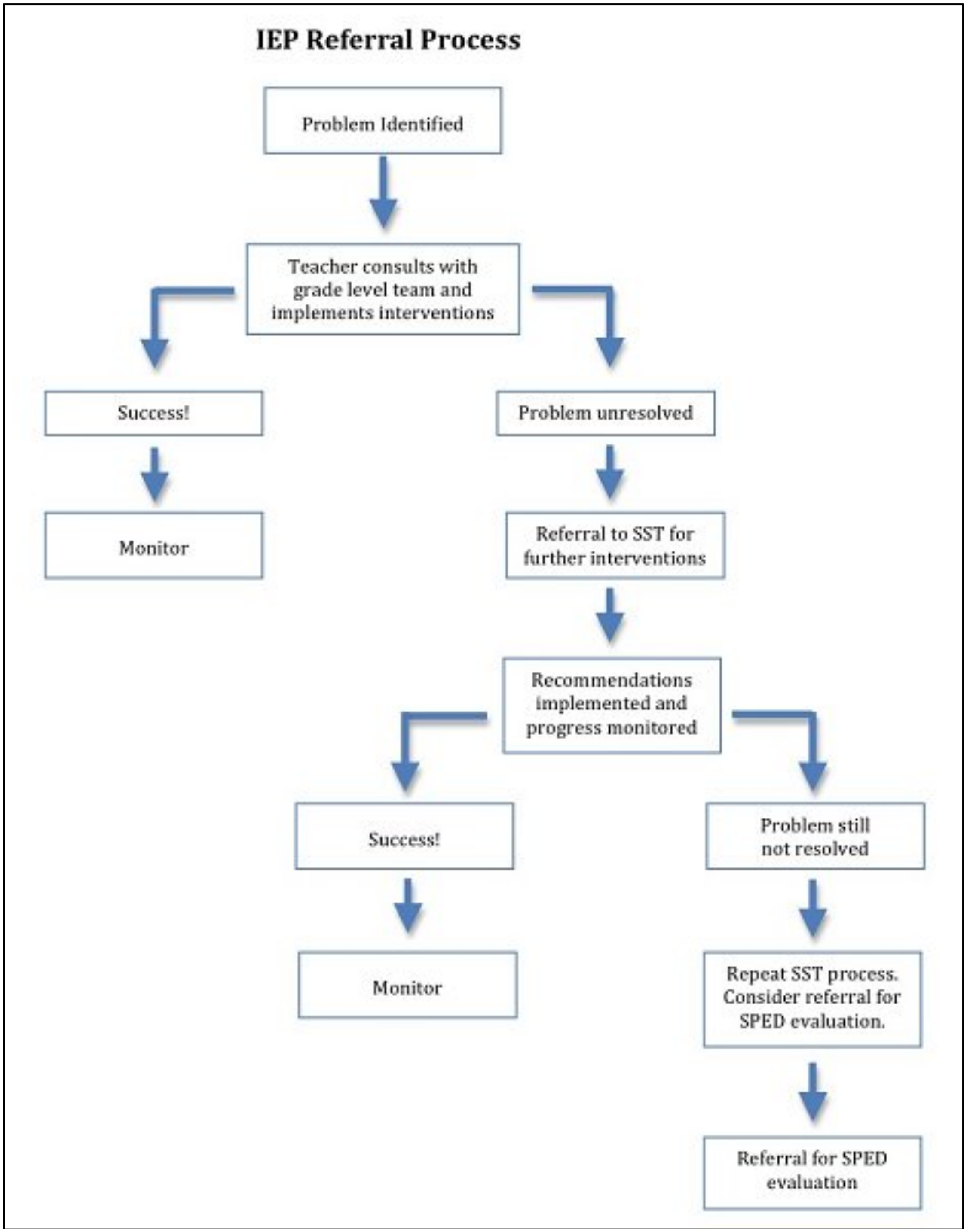
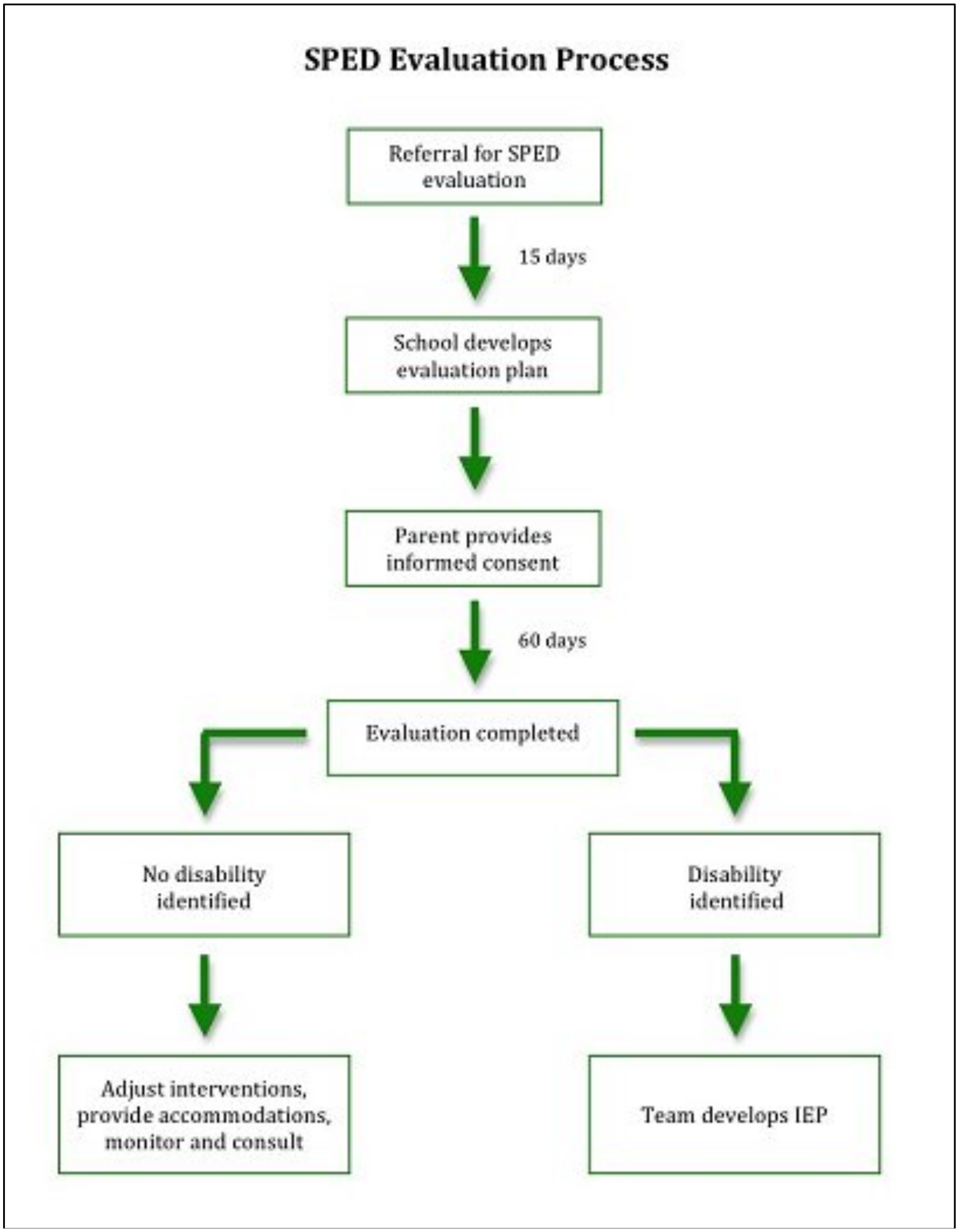
Tables and Figures

Figure 1. California Special Education Referral and Evaluation Process

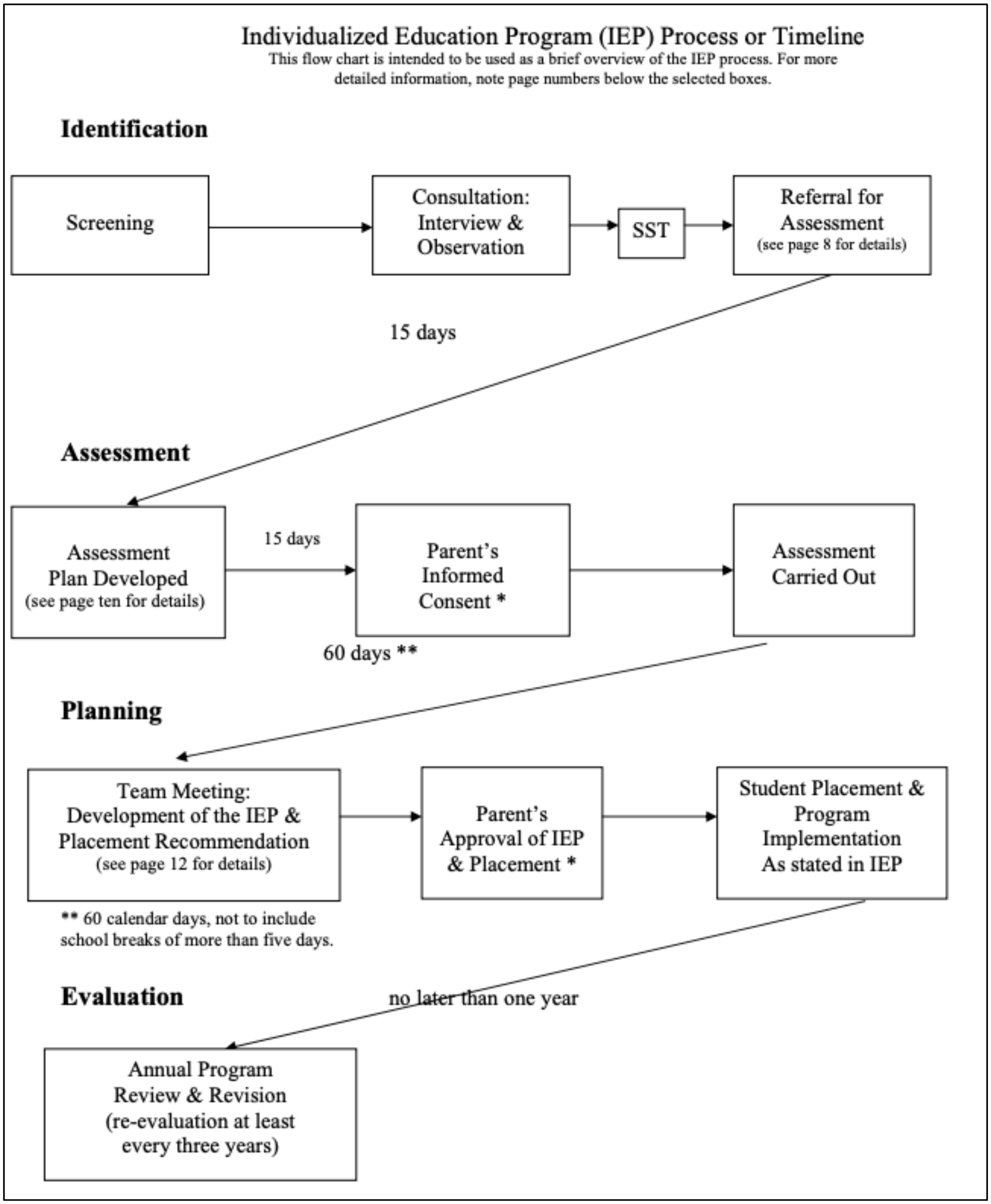


(Figure 1., continued)



Note: Diagrams taken from the Cardiff School District in California (https://www.cardiffschools.com/Page/26). SST refers to a "Student Support Team," typically made up of special education teachers and interventionists.

Figure 2. Nevada Special Education Referral and Evaluation Process



Note: Diagram taken from the Nevada County Special Education Parent Advisory Committee (http://nevco.org/wp-content/uploads/2013/09/ParentHandbookNevCoSELPA.pdf).

Figure 3. Overall Special Education Identification Rates in California and Nevada

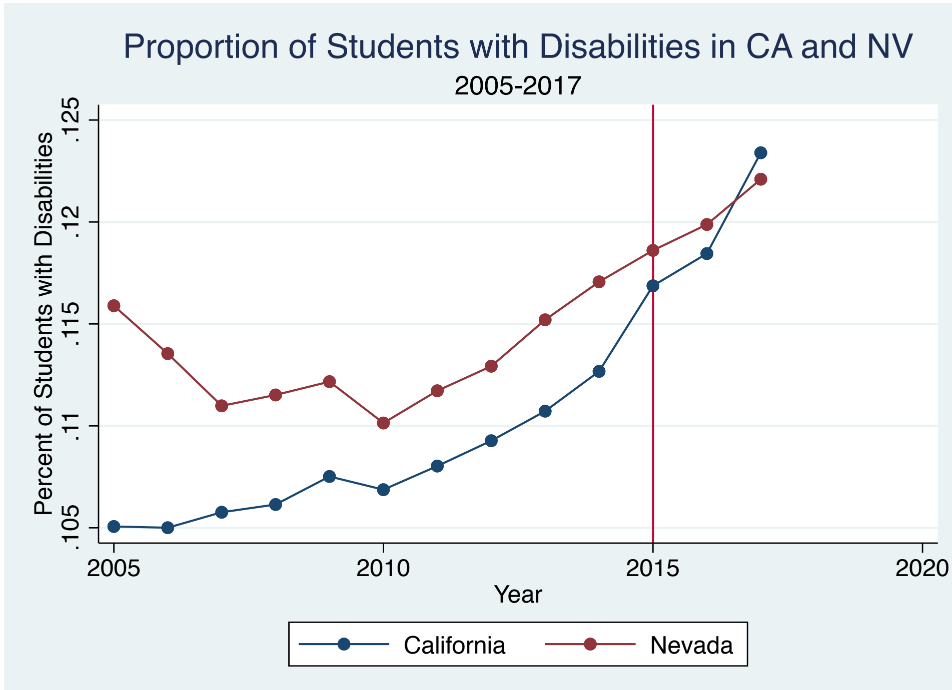


Figure 4. Special Education Identification Rates in California and Nevada for Subjective Disabilities

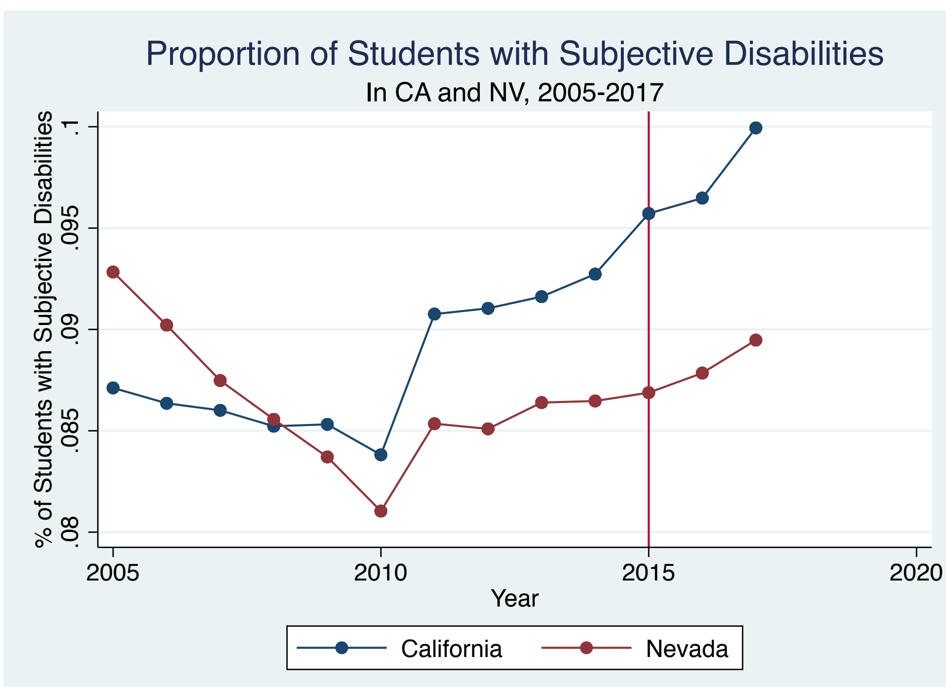


Figure 5. Subjective Disability Identification Rates in California

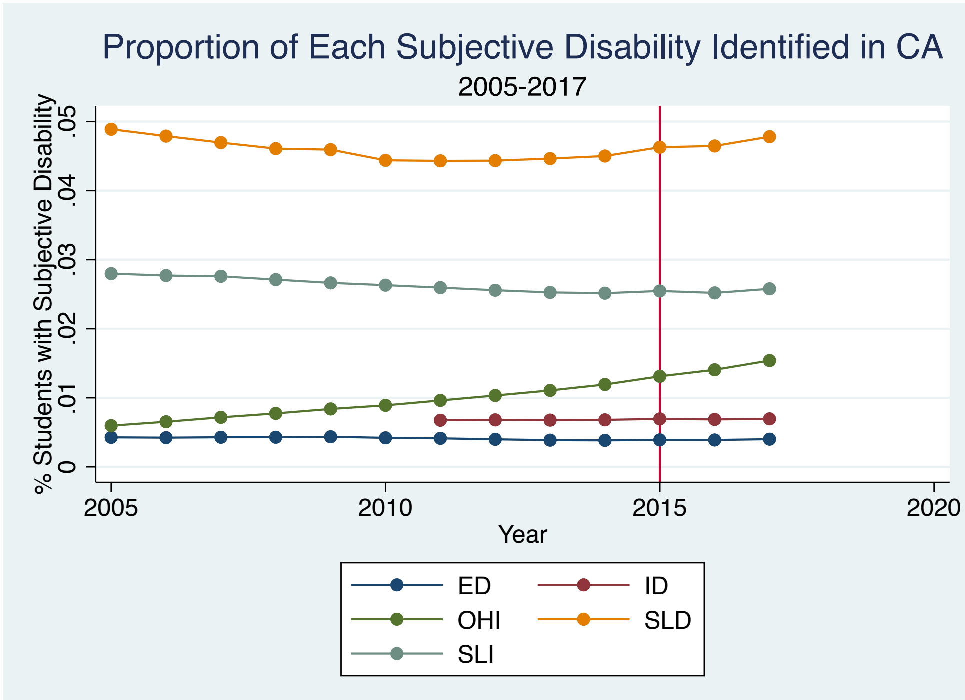


Figure 6. Subjective Disability Identification Rates in Nevada

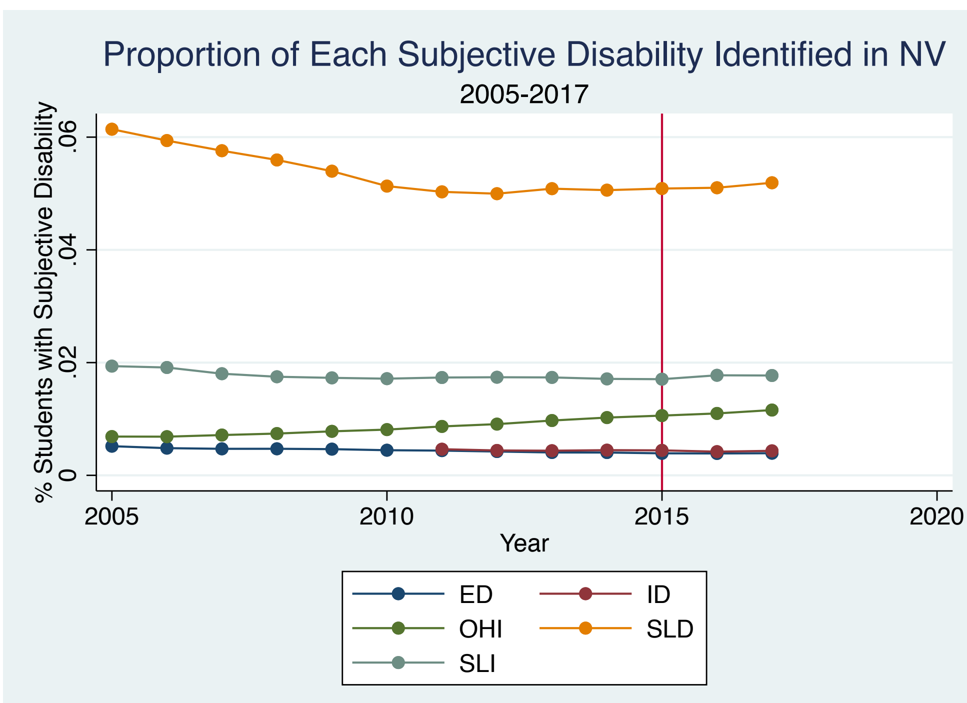


Table 1. Summary Statistics

Year	California			Nevada		
	Total # SPED Students (Age 3-21)	Total # Public School Students	% SPED	Total # SPED Students (Age 3-21)	Total # Public School Students	% SPED
2005	676,318	6,437,202	10.5%	47,794	412,395	11.6%
2006	672,737	6,406,750	10.5%	48,230	424,766	11.4%
2007	670,904	6,343,471	10.6%	47,652	429,362	11.1%
2008	671,095	6,322,528	10.6%	48,328	433,371	11.2%
2009	673,428	6,263,438	10.8%	48,115	428,947	11.2%
2010	672,174	6,289,578	10.7%	48,148	437,149	11.0%
2011	679,269	6,287,834	10.8%	49,117	439,634	11.2%
2012	688,346	6,299,451	10.9%	50,332	445,707	11.3%
2013	698,947	6,312,623	11.1%	52,052	451,831	11.5%
2014	711,205	6,312,161	11.3%	53,755	459,189	11.7%
2015	727,718	6,226,737	11.7%	55,452	467,527	11.9%
2016	747,317	6,309,138	11.8%	56,791	473,744	12.0%
2017	767,562	6,220,413	12.3%	60,123	492,416	12.2%

Table 2. Difference-in-Differences Results for Overall Special Education Identification Rates and Identification Rates for Subjective Disabilities

	Overall Trends in SPED Identification			Adding Demographic Controls			Limited to Subjective Disabilities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	% SPED Ages 3-5	% SPED Ages 6-21	% SPED Ages 3-21	% SPED Ages 3-5	% SPED Ages 6-21	% SPED Ages 3-21	% Subjective Disability Ages 3-5	% Subjective Disability Ages 6-21	% Subjective Disability Ages 3-21
State*Post Interaction	0.000661	-0.00567**	-0.00501*	-0.00419	0.00244	-0.00175	-4.68e-06	-0.000384**	-0.000389**
	(0.000817)	(0.00228)	(0.00252)	(0.00245)	(0.00281)	(0.00249)	(2.84e-06)	(0.000142)	(0.000143)
State	0.00457***	0.000512	0.00508***	-0.275	-0.0821	-0.357	-9.33e-06***	0.000355**	0.000345**
	(0.000771)	(0.00125)	(0.00143)	(0.229)	(0.373)	(0.258)	(2.24e-06)	(0.000134)	(0.000134)
Post-2015	0.00168***	0.0107***	0.0124***	0.00129	-0.00102	0.000273	-5.53e-07	-0.000174**	-0.000174**
	(0.000341)	(0.00190)	(0.00222)	(0.00158)	(0.00242)	(0.00242)	(1.66e-06)	(7.38e-05)	(7.47e-05)
Demographic Controls	No	No	No	Yes	Yes	Yes	No	No	No
Constant	0.0115***	0.0971***	0.109***	0.313	0.190	0.503	1.56e-05***	0.00411***	0.00412***
	(0.000229)	(0.000942)	(0.00114)	(0.248)	(0.404)	(0.281)	(5.74e-07)	(5.97e-05)	(5.97e-05)
Observations	26	26	26	18	18	18	26	26	26
R-squared	0.718	0.580	0.679	0.937	0.898	0.982	0.573	0.383	0.376

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Difference-in-Differences Results Disaggregated by Race, Gender, and English Language Learner Status

	Differential Outcomes by Race							By Gender		For ELLs
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Dependent Variable	% American Indian / Alaska Native with Disabilities	% Asian with Disabilities	% Black with Disabilities	% Hispanic with Disabilities	% White with Disabilities	% Native Hawaiian / Pacific Islander with Disabilities	% Two or More Races with Disabilities	% Female with Disabilities	% Male with Disabilities	% ELL with Disabilities
State*Post Interaction	-0.000608	-0.00136***	0.00200***	-0.00267	-0.00417*	0.000190*	4.62e-06	-0.000811	-0.00269	0.00421**
	(0.000796)	(0.000353)	(0.000470)	(0.00290)	(0.00202)	(9.20e-05)	(0.000715)	(0.00115)	(0.00206)	(0.00147)
State	0.00132	-0.00320***	0.00501***	-0.0168***	0.0173***	0.000517***	0.00248***	0.00195**	0.00162	-0.0110***
	(0.000795)	(0.000289)	(0.000393)	(0.00252)	(0.00201)	(9.07e-05)	(0.000667)	(0.000719)	(0.00146)	(0.00139)
Post-2015	-0.000607	0.000903***	-0.0010***	0.0131***	-0.00289***	-1.35e-05**	0.00158***	0.00301**	0.00553**	0.000408
	(0.000610)	(0.000247)	(0.000277)	(0.00235)	(0.000991)	(5.42e-06)	(0.000352)	(0.000972)	(0.00179)	(0.000454)
Demographic Controls	No	No	No	No	No	No	No	No	No	No
Constant	0.00146**	0.00675***	0.0110***	0.0552***	0.0319***	0.000472***	0.00303***	0.0359***	0.0765***	0.0339***
	(0.000610)	(0.000156)	(0.000274)	(0.00193)	(0.000980)	(4.88e-06)	(0.000299)	(0.000579)	(0.00117)	(0.000283)
Observations	25	25	25	25	25	17	17	12	12	12
R-squared	0.180	0.901	0.925	0.800	0.824	0.860	0.722	0.778	0.651	0.936

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1