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Career and Technical Education, Inclusion, and Postsecondary Outcomes for Students with Disabilities

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Abstract

We use longitudinal data on all high school students in Washington State, including postsecondary education and workforce outcomes, to investigate predictors of intermediate and postsecondary outcomes for students with disabilities. We pay particular attention to career and technical education (CTE) enrollment and the extent of inclusion in general education classrooms, as prior research suggests these factors may be particularly important in influencing the outcomes of students with disabilities. We estimate models that compare students with other students within the same school district, who are receiving special education services for the same disability, and have similar baseline measures of academic performance and other demographic information. We find generally weak relationships between CTE enrollment in any particular grade and intermediate and postsecondary outcomes for students with disabilities, though we replicate earlier findings that students with disabilities who are enrolled in a "concentration" of CTE courses have higher rates of employment after graduation than students with disabilities who are similar in other observable ways but are enrolled in fewer CTE courses. We also find consistently strong evidence that students with disabilities who spend more time in general education classrooms experience better outcomes—fewer absences, higher academic performance, higher rates of grade progression and on-time graduation, and higher rates of college attendance and employment—than students with disabilities who are similar in other observable ways but spend less time in general education classrooms.

1. Introduction

Each year, nearly 6.5 million public school students (approximately 13% of all students enrolled in public education) receive special education services as part of the Individuals with Disabilities Education Act (IDEA) (National Center for Education Statistics, 2016). This represents a tremendous federal investment in special education services—approximately $50 billion annually (Morgan, Frisco, Farkas, & Hibel, 2010). The 2004 reauthorization of IDEA placed greater emphasis on using these funds to improve the postsecondary outcomes (including “training, education, employment, and, where appropriate, independent living skills”) of students receiving special education services, and the US Department of Education Office of Special Education Programs has identified post-school outcomes as a monitoring priority.

The more than a decade since the reauthorization of IDEA has seen a burgeoning literature that uses administrative data to investigate the factors influencing postsecondary outcomes for public school students in general, but students with disabilities have received far less empirical attention. This fact is surprising given the amount of funding invested into special education, the number of students receiving these services, and mounting descriptive evidence (discussed in Section 2) that students with disabilities continue to lag behind their peers in terms of K–12 outcomes, college attendance, and employment success.

This study uses detailed administrative data on public school students in Washington State, linked to postsecondary education and employment data for these students, to examine how two malleable factors (i.e., potentially policy-manipulable variables) predict both intermediate and postsecondary outcomes for high school students with disabilities. These malleable factors are (a) enrollment in career and technical education (CTE) courses; and (b) the percentage of the school day spent in general education classrooms (“inclusion”).[1] Using these factors, this study investigates three broad, descriptive research questions:

1. What malleable factors are predictive of intermediate outcomes (unexcused absences, test performance, and persistence/graduation) for students with disabilities?
2. What malleable factors are predictive of the postsecondary success (college enrollment and employment) of students with disabilities?
3. Which intermediate outcomes may mediate the relationship between these malleable factors and measures of postsecondary success?

Research question 1 connects the malleable factors described above to a number of intermediate outcomes that are generally thought to predict student postsecondary success. Specifically, we quantify the following intermediate outcomes: (a) the number of unexcused absences in 10th, 11th, and 12th grade; (b) test scores on 10th-grade math and reading tests; and (c) persistence in and graduation from high school.[2] In research question 1, we consider these variables as outcome variables; for example, does CTE enrollment predict absences, 10th-grade achievement, and grade persistence and graduation? In research question 3, we revisit these intermediate variables to examine whether they are also potential mediators in the relationships between the malleable factors above and measures of the postsecondary success of students with disabilities.

For research question 2, we focus on the direct relationship between malleable factors and postsecondary outcomes. Our data allow us to quantify two measures of students’ postsecondary

[1] We consider these variables to be malleable because policymakers can offer more CTE courses or allocate resources to support inclusion; however, participation in CTE and inclusion will depend on the student’s interest, situation, IEP team, and other factors that may moderate the effects of policy.
[2] The relationship between each of these intermediate outcomes and postsecondary outcomes have been thoroughly researched; see Gottfried (2009) for a discussion on absences, Rose (2006) for a discussion of test scores, and Heckman et al. (2006) for cognitive and non-cognitive outcomes.

success: (a) enrollment in a two-year or four-year college and (b) employment in the state workforce.[3] These outcome measures are motivated by research demonstrating that students with disabilities lag behind their peers in terms of each of these measures of postsecondary success (see Section 2 on prior literature); in short, students with disabilities are less likely to attend college and less likely to be employed than students without disabilities. We first document the postsecondary success of students with disabilities in Washington State along these dimensions and compare these average outcomes with measures of the postsecondary success of all public school students in Washington State. However, our primary focus in research question 2 is to connect these measures of postsecondary success to malleable factors and intermediate outcomes at the high school level that may be predictive of these important outcomes.

In research question 3, we investigate whether our intermediate outcomes of interest mediate the relationships described in research question 2. For example, we investigate whether the relationship between CTE enrollment and college attendance may be partially or entirely explained by student absences, test scores, and/or on-time grade progression. These results are important for future research that may not have access to postsecondary data by answering the question, "To what degree do relationships between malleable factors and intermediate outcomes capture relationships with postsecondary outcomes?" For example, if researchers only have access to test score data and this intermediate outcome does not fully mediate the relationship between CTE enrollment and postsecondary outcomes, then results based solely on test score give an incomplete picture of these long-term patterns.

We find generally weak relationships between CTE enrollment in any particular grade and intermediate and postsecondary outcomes for students with disabilities. That said, when we adopt the

[3] Our data also include information about incarceration in state penitentiaries from the Washington State Department of Corrections, but the number of students incarcerated during the years of data considered in this study was too small to consider this outcome in the analysis.

approach of Wagner et al. (2016) and consider students with disabilities who take a "concentration" of CTE courses in high school (defined as taking at least four credits of CTE courses), we replicate the finding in Wagner et al. (2016) that these students are more likely to be employed after graduation than similar students with disabilities who take fewer CTE courses.

We also find consistently strong evidence that students with disabilities who spend 80% to 100% of the school day in general education classrooms experience better outcomes than students with disabilities who experience less inclusion, all else equal. Specifically, students with disabilities who spend 80% to 100% of the school day in general education classrooms have fewer absences, higher academic performance, higher rates of grade progression and on-time graduation, and higher rates of college attendance and employment than students with disabilities who are similar in other observable ways but spend less time in general education classrooms.

It is important to be cautious about the interpretation of the above findings. We estimate analytic models intended to create "apples-to-apples" comparisons between students with disabilities who have similar baseline levels of achievement, other observable characteristics, and (in some specifications) who are attending the same district or school, but these students may be different in unobserved ways that correlate with their high school experiences (e.g., Goldberger & Cain, 1982). For example, more career-oriented students with disabilities could be more likely to enroll in CTE courses relative to students with disabilities who are similar in observable ways who do not participate, and this type of selection would bias our estimates of the impact of CTE enrollment on student outcomes if the observable characteristics in our models do not capture these unobserved factors.

We pursue a number of different extensions and robustness checks that consistently support our primary findings, but given that we cannot fully account for all the different potential sources of bias, we ultimately view these results as descriptive. That said, the relationships between inclusion in general education classrooms and subsequent outcomes are sufficiently consistent across specifications and outcomes to suggest that students with disabilities receive benefits from inclusion that impact their future outcomes.

A final contribution of this paper is that we illustrate the importance of controlling for student characteristics—in particular, prior test scores—when estimating the relationships between CTE enrollment, inclusion, and student outcomes. Most of the empirical literature discussed in the following section does not control for these potential confounders, and we demonstrate that omitting these controls overstates the impact of inclusion in our sample by 51 to 116 percent for college enrollment, and 23 to 47 percent for postsecondary employment. Interestingly, our estimates of the relationships between CTE enrollment and postsecondary outcomes appear to be less sensitive to the inclusion of these controls, which is consistent with the notion that nonrandom selection bias is less of a concern for CTE enrollment than inclusion.

The remainder of the paper proceeds as follows. Section 2 reviews the prior literature related to research questions 1–3, whereas Section 3 describes in detail the data set used in this study. We outline our analytic approach in Section 4, describe our results in Section 5, and conclude with some potential policy implications in Section 6.

2. Prior Literature

A number of studies have examined postsecondary outcomes for students with disabilities. Instead of providing a comprehensive overview of this literature, we start by briefly discussing descriptive research on postsecondary outcomes for students with disabilities to give a sense of the overall disparities in outcomes. We then focus on studies that estimate the relationship between CTE enrollment, inclusion, and postsecondary outcomes, and discuss how the samples and methods used compare to those in this study.

Much of the existing literature documents average intermediate and postsecondary outcomes for students with disabilities and compares these average outcomes to outcomes for other public school students. For example, a series of papers by Wagner and colleagues (Wagner 1992, 1993; Wagner, Newman, Cameto, Garza, & Levine, 2005; Wagner, Newman, Cameto, Levine, & Garza, 2006; Newman, Wagner, Cameto, Knokey, & Shaver, 2010) provides descriptive statistics on employment and postsecondary education outcomes for students with disabilities from two waves of the National Longitudinal Study of Special Education Students. These studies consistently report that students with disabilities lag behind other public school students in terms of these measures of postsecondary success. Affleck, Edgar, Levine, and Kortering (1990), Karpinski, Neubert, and Graham (1992), Murray, Goldstein, Nourse, and Edgar (2000), and Rabren, Dunn, and Chambers (2002) provide similar descriptive statistics and conclusions from surveys of other, smaller subgroups of students from different states across the country. Our paper contributes to this body of research by providing the first descriptive evidence about employment and college enrollment for students with disabilities that uses a statewide administrative database that includes all students with disabilities in a state.

While we build on this existing descriptive evidence of postsecondary outcomes for students with disabilities, our larger goal is to connect these outcomes to malleable factors and intermediate outcomes at the high school level. There are a few existing studies that do this, though they are often small-scale case studies. For example, Hasazi, Gordon, and Roe (1985) and Baer et al. (2003) both find that CTE enrollment is predictive of employment success for former special education students, and similarly, Baer et al. (2003) and Mithaug, Horiuchi, and Fanning (1985) find correlations between inclusion and postsecondary education and employment success. Rea, McLaughlin, and Walther-Thomas (2002) also find that inclusion is associated with better test scores, behavior, and attendance in high school. However, the small sample sizes in these studies (often fewer than 100 students) raise questions about the generalizability and robustness of these findings.[4] In contrast, our research focuses on a much larger sample of special education students in Washington State (56,915 student-year observations).

A few larger-scale studies connect malleable factors to postsecondary outcomes; most of these focus on estimating the effects of CTE enrollment. Benz, Lindstrom, and Yovanoff (2000), Harvey (2002), and Sitlington and Frank (1990) all find that CTE enrollment is predictive of employment success, postsecondary education, or both. These findings are reinforced in a review by Test et al. (2009), who find that—among 16 evidence-based, in-school predictors of the postsecondary success of students with disabilities—CTE enrollment is consistently predictive of postsecondary outcomes. Haber et al. (2015) conducted a meta-analysis to provide further evidence on the predictors identified by Test et al. (2009) and found that CTE enrollment had no correlation with education outcomes, but was positively predictive of employment, and that inclusion was a larger predictor than typically found in the literature.[5] Finally, Mazzotti et al. (2016) provided a systematic review that extended past 2009, a period that included the release of the National Longitudinal Transition Study-2 data widely used to study the post-secondary outcomes of students with disabilities. They found additional support for 9 of the factors studied by Test et al. (2009), with inclusion and CTE enrollment continuing to be predictive of education and employment outcomes.

That said, a significant shortcoming of these studies (or many of the studies considered in these meta-analyses) is that they do not control for baseline measures of student achievement or other nonschooling factors (like participation in free or reduced-price lunch programs) that may confound the relationship between CTE enrollment, inclusion, and postsecondary success. We attempt to address this

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[4] Hasazi, Gordon, and Roe (1985) conduct interviews of 301 students with disabilities from nine Vermont school districts; Baer et al. (2003) analyze data from phone surveys and record reviews of 140 randomly selected students with disabilities in Ohio; Mithaug, Horiuchi, and Fanning (1985) surveyed 234 graduates in Colorado; Rea, McLaughlin, and Walther-Thomas (2002) examine quantitative and qualitative data on 8th grade students from two anonymous middle schools.

[5] CTE participation had positive impacts on employment but not education, while Transition programs had positive impacts on education but not employment.

potential shortcoming by using administrative records of student achievement and program participation as controls for baseline achievement and other nonschooling factors when assessing the relationship between these malleable factors and postsecondary outcomes.

A few studies focus on predictors of postsecondary outcomes for students with disabilities while controlling for baseline measures of student achievement and other student demographic characteristics. Wagner (1991) considers both CTE enrollment and inclusion as malleable factors that could predict the intermediate and postsecondary success for students with disabilities, and she uses data from the National Longitudinal Study of Special Education Students to estimate models that include controls for baseline performance measures (functional mental skills and IQ score) and household characteristics (single-parent and household income). The estimates from these models suggest that both CTE enrollment and inclusion are correlated with secondary school performance, graduation, education, employment, and personal independence, all else equal. In contrast, Heal and Rusch (1995) use the same data set to investigate employment outcomes for students with disabilities but find that school programs for these students (including CTE enrollment) “had minimal effect on postschool employment once student competence and family characteristics had been controlled for.” These disparate findings may be due to methodological differences—Wagner (1991) included all student controls in all models, whereas Heal and Rusch (1995) used forward selection to select their control variables—but more importantly, the evidence from these papers is now approximately 20 years old.[6] Most recently, Wagner, Newman, and Javitz (2016) reexamine this issue with a longer panel of data and propensity score matching on baseline performance and family characteristics; they find that students with learning disabilities who participate in a “concentration” of CTE courses are more likely to be employed within two years of leaving high school, but not in later years.

[6] This is important because federal support and requirements for CTE changed with the introduction of the Carl D. Perkins Career and Technical Education Improvement Act of 2006 in order to improve accountability and provide $1.1 billion of funding through 2012 (Dortch, 2012).

Recent work by Michael Gottfried and colleagues (Gottfried, Bozick, Rose, & Moore, 2016; Plasman & Gottfried, 2016) considers specific aspects of CTE programs—applied STEM coursework and school-based experiential programs—as predictors of longer-term outcomes for students with disabilities. Although Plasman and Gottfried (2016) find that applied STEM courses are predictive of better outcomes for students with learning disabilities (e.g., lower dropout rates, higher test scores, higher rates of postsecondary enrollment), Gottfried et al. (2016) reported that these aspects of CTE courses are more predictive of progression through the STEM pipeline for students without disabilities. These differences may be due to the different data sources of the two studies; Plasman and Gottfried (2016) use the Educational Longitudinal Study of 2002, whereas Gottfried et al. (2016) use the National Longitudinal Survey of Youth 1997.

3. Data and Summary Statistics

Student data and control variables

The data for this project are maintained by Washington State's Education Research and Data Center (ERDC), a P–20 student data warehouse that combines administrative K–12 data with college and employment data. The K–12 data come from Washington State's Comprehensive Education Data and Research System (CEDARS), a longitudinal data system introduced in the 2009–10 school year. This data system links four primary files: a student enrollment and program file that includes detailed data about special education services; a student schedule file that includes one entry for each student and course in which the student is enrolled; a teacher schedule file that includes one entry for each teacher and course the teacher is assigned to teach; and the Washington State S-275 personnel report that includes demographic, experience, and salary data for each teacher in the state. Although the CEDARS data system was introduced in the 2009–10 school year, it can be linked to some of the data sets that preceded it, such as test scores and previous school enrollment records, which allow for baseline controls for student test achievement.

We supplement this data set with the P-210, an annual federal enrollment compliance report constructed by state's Office of Superintendent of Public Instruction from the CEDARS data. The P-210 contains the final record of enrollment status (e.g., graduate, dropout, continue on to the next grade) for each student from the prior school year. Using the P-210 for available school years (2008–09 through 2011–12) and the CEDARS enrollment data for the later school years (2012–13 and 2013–14), we construct a student-year level data set with grade and enrollment status at the end of the year.[7] We then merge on student characteristic indicators including race/ethnicity, housing status, migrant status, gender, free or reduced-priced lunch eligibility, learning disability status, and program participation in English language learning, part-time home schooling, and gifted/highly capable programs. This student-year data set is linkable at all other student, school,[8] district, or teacher data sets and variables mentioned below.

The CEDARS enrollment data also contain 15 different codes for student disabilities; these disability codes are listed in **Table 1.**[9] The most common disability type in our sample is a specific learning disability (SLD). SLD is defined by IDEA as "a disorder in 1 or more of the basic psychological processes involved in understanding or in using language, spoken or written, which disorder may manifest itself in the imperfect ability to listen, think, speak, read, write, spell, or do mathematical calculations." Identification is based on either a "severe discrepancy" in academic performance or failure to improve as part of a Response To Intervention (RTI) model. The second most common

[7] Because the P-210 is what Washington State reports to the federal government, we use it for all years in which it is available to us. We discuss how well the P-210 and the CEDARS enrollment data correspond in our description of transition outcomes**.**

[8] Students occasionally switch schools throughout the year and this may impact their enrollment in particular programs. This presents challenges for modeling data at the student-year level. To address this, all student characteristics that are linkable to schools are determined at the school in which the student spent the most days attending in any given year.

[9] Two disability types, developmental delays and deaf-blindness, are not reported because of small cell sizes.

disability type in our sample is a health impairment that is due to chronic or acute health problems, such as asthma, attention deficit disorder, or Tourette syndrome, which adversely affects the student's academic performance. The remaining disability classifications include autism, deafness, or communication disorders.

We use these disability types in three ways in our analysis. First, we include disability type indicators in all analytic models so that students with disabilities are compared only with students with the same disability type. Second, we extend our primary analysis by investigating trends separately for students receiving special education services for different disability types; because of small sample sizes within most disability types, we most frequently compare results for students with an SLD to results for students receiving special education services for another disability type. Finally, we construct a cumulative sum of the number of years a student is diagnosed with a disability from seventh grade until the current school year as a proxy for prior years of special education services.

Because we have detailed special education data starting in 2009–10 linked to postsecondary data through 2013–14, we are able to consider two cohorts of students from 10th grade through one year beyond their expected high school graduation year. Within each cohort—students who are enrolled in 10th grade for the first time in 2009–10 ("Cohort 1") and students who are enrolled in 10th grade for the first time in 2010–11 ("Cohort 2")—we define the sample in subsequent grades as students who are still "on track" to graduate on time (i.e., 11th graders in each cohort consist only of students from the 10th-grade sample who proceeded to 11th grade the following year). **Table 1** shows the number of students in each grade, year, and cohort according to disability type. Approximately 10.6% (16,003 of 150,438) of all unique students across the two cohorts are receiving special education services in 10th grade. Of students diagnosed with a disability in 10th grade, 65.2% are still in the data and receiving special education services in 12th grade. Of the 34.8% of students with disabilities who are no longer in the sample in 12th grade, 7.9% appear to have dropped out, 14.7% do not have course information in later grades, 5.9% have transferred out of the Washington State public school system, and 6.2% are no longer receiving special education services.

For the remainder of the paper, we combine data from these two cohorts of students to create a single analytic sample. Panels A and B of **Table 2** present summary statistics pooled across both cohorts at the student-year level and for Grades 10–12, unless otherwise specified. Panel A of **Table 2** illustrates that students with disabilities in the sample are much more likely to be male, an underrepresented minority (American Indian, Black, or Hispanic), and receiving free or reduced-price lunch relative to students without disabilities. Moreover, students with a specific learning disability are more than twice as likely to be classified as an English language learner than students receiving special education services for a different disability.

Our primary measure of baseline performance comes from Washington State's Student Testing Database, which includes eighth-grade test scores for all of our cohorts on the Washington Assessment of Student Learning (WASL).[10] The WASL is composed of subject-specific tests in science, reading, and math.[11] All of the WASL scores used in our models and reported here have been standardized across all test takers within grade and year.[12] Panel B of **Table 2** illustrates that students with disabilities have much lower levels of baseline achievement than students without disabilities, and the gaps range from approximately 1.3 to 1.4 standard deviations.

Malleable Factors

The K–12 experiences of students with disabilities can vary along a number of dimensions that may influence their postsecondary success. We focus on two of these malleable factors as the "treatment variables" in our analysis. These factors are malleable, in that school leaders could intervene

[10] We include both the WASL and WASL-Basic. The WASL-Basic is the same test as the WASL, but students with disabilities who take this test can pass with a lower score.
[11] The WASL was renamed in 2009–10 as the Measures of Student Progress and replaced by the Smarter Balanced Assessment in the 2014–15 school year. Neither of these changes effect these eighth-grade measures for our sample.
[12] Due to a data error in the data provided by ERDC, assessment data in 2009 are missing for students from approximately 15% of districts.

on these variables to try to improve outcomes for students with disabilities. The first malleable factor is enrollment in career and technical education (CTE) courses, which the CEDARS student schedule file classifies via Classification of Instructional Program (CIP) codes.[13] Panel C of Table 2 illustrates that approximately two-thirds of all students in the sample are enrolled in at least one CTE course in a given year under this definition, and that students with a SLD are particularly likely to be enrolled in at least one CTE course. Looking across all years of data, 85.9% of 10th graders take at least one CTE course during the duration of their high school career, and 93.9% of graduates took at least one CTE course between 10th and 12th grade.

Second, we use the "least restrictive environment" (LRE) code in the CEDARS student enrollment and programs file, indicating the percentage of the school day (80% to 100%, 40% to 79%, or less than 40%) each student spends in general education classrooms, to create a measure of the extent of each student's inclusion in general education classrooms. Panel D of Table 2 summarizes the distribution of LRE codes. Approximately 46% of all students with disabilities (and 52% of students with a SLD) spent at least 80% of the school day in general education classes, whereas another 41% (44% of students with a SLD) spent between 40% and 79% of the school day in general education classrooms.[14] In our primary models, compare students with disabilities spending at least 80% of the school day in general education classes to students with disabilities who spend less time in general education classrooms.[15]

Intermediate Outcomes and Potential Mediators

The K–12 data system provides data on each of our three intermediate outcomes: the number of unexcused absences, test scores on 10th-grade math and reading tests, and persistence in and

[13] Roughly 10% of high school students are missing schedule data, but are still the CEDARS enrollment file. We limit our analyses to students with both enrollment and schedule data, so results are only generalizable to this group of students.

[14] Approximately 15% of students with disabilities are missing LRE codes in the data provided by ERDC. We focus only on students with disabilities who have LRE codes in our inclusion analysis.

[15] For context, 24% of the classmates of students with disabilities who spend more than 80% of the school day in general education classrooms are enrolled in special education, compared to 45% of the classmates of students with disabilities who spend less than 80% of the school day in general education classrooms.

graduation from high school. Each of these outcomes is potentially influenced by the malleable factors discussed above and potentially influences the postsecondary success of students with disabilities. Therefore, each of these intermediate outcomes is also a potential mediator in the relationship between our malleable factors and a student's postsecondary success.

The K–12 CEDARS student enrollment file includes the number of unexcused absences for each student in each year. Student absences are an important intermediate outcome because they are highly correlated with student performance (e.g., Gottfried, 2009) and later outcomes (e.g., Allensworth & Easton, 2007). Panel A of **Table 3** illustrates that students with disabilities have, on average, more unexcused absences than students without disabilities, and that the gap increases across each grade. The apparent trend in an increasing number of absences across grades (regardless of disability status) reflects two important and distinct trends. First, within any given year students tend to have more absences in later grades. Second, within the same grade the number of absences grows across years.[16] Because observations of students in 12th grade take place in later years, this contributes to the trend of more unexcused absences in 12th grade than 10th grade. We account for these trends in our models by standardizing the number of absences with years and estimating models within specific grades.

Nearly every 10th-grade student in 2009–10 and 2010–11 took a standardized test in math and/or reading at the end of the year. For reading, the test in both years was the High School Proficiency Exam (HSPE). In 2009–10, students also took the HSPE math subtest. However, in 2010–11, students began taking end-of-course exams specific to the math course they were enrolled in that year (Algebra or Geometry). All test scores have been standardized by year, grade, subject, and specific test. Panel B of Table 3 illustrates that, as in eighth grade, students with disabilities perform substantially worse on these tests than students without disabilities.

[16] This trend appears to be largely driven by either a data error or a change in reporting standards. Starting in 2012, the average number of unexcused absences jumps significantly because fewer students have zero unexcused absences.

As mentioned earlier, the P-210 contains a "student enrollment" field for each student that includes the following possible outcomes: "Completer Codes" (graduated with a regular high school diploma, confirmed receipt of GED certificate, confirmed completion of individualized education program, confirmed completion of Adult High School Diploma); "Confirmed Transfer Codes" (confirmed transfer out of the district, confirmed transfer out of the school within district); and "Dropout Codes" (e.g., expelled or suspended and did not return, attendance for four years or more and did not graduate, etc.). Because the P-210 is generated from the CEDARS enrollment data, the enrollment data also contain these same "student enrollment" codes.[17] By using these two data sets, we can construct a variable measuring whether a student progresses to the next grade or graduates on time.[18]

Panel C of Table 3 reports grade progression and graduation statistics by disability status. For example, 59.6% of 10th graders in the two cohorts with a diagnosed disability graduate on time, compared with 83.8% of students without disabilities. This finding is comparable with graduation rates for students with disabilities reported elsewhere in the literature (e.g., 56% in Wagner, 1991). Importantly, Table 3 illustrates that the graduation gap between students with and without disabilities is driven primarily by 12th graders; grade progression rates are roughly comparable between the two groups through 12th grade, but 12th graders with disabilities are more than 20 percentage points less likely to graduate at the end of the year than other 12th graders (71.4% vs. 92.0%). This gap closes somewhat when we consider the five-year graduation rate of 12th graders (82.0% vs. 94.8%).

Postsecondary Measures of Success

[17] Although we do not have access to the P-210 for the 2012–13 and 2013–14 school years, Washington State does. To ensure we are consistently coding on-time graduation across these two data sets, we compare our graduation rates from these two years with those reported by Washington State. Using the CEDARS enrollment data, we report a four-year on-time graduation rate of 75% for the 2012–13 school year and 79% for the 2013–14 school year. The corresponding rates produced by Washington State using the P-210 are 76% and 77%.

[18] At the end of 10^{th} or 11^{th} grade, we only consider a student as not progressing to the next grade if they have one of the "Dropout Codes". In 12^{th} grade, we consider a student as not graduating if they do not have one of the "Completer Codes".

In the introduction, we identified two measures of postsecondary success for students with disabilities: enrollment in an in-state, public two-year or four-year college and employment in the state workforce. We can consider these postsecondary outcomes because of unique student identifiers in the data sets provided by ERDC that connect students in CEDARS K–12 data set with data from the state's colleges: the Public Centralized Higher Education Enrollment System (PCHEES) for public, four-year universities in Washington State and the State Board of Community and Technical Colleges (SBCTC) data system for public two-year colleges in Washington State.[19] An important caveat is that these data sets do not cover out-of-state colleges or in-state private colleges.[20]

Using these data systems, we created a variable for each student that indicates whether the student enrolled in a public in-state college within six months after their expected graduation. Panel D of Table 3 presents college enrollment statistics by disability status for 10th graders, as well as enrollment statistics conditional on graduation. Interestingly, the two-year college enrollment rate of on-time graduates is similar for high school graduates with and without disabilities (19.3% vs. 22.1%). However, the four-year college enrollment rates of high school graduates vary considerably by disability status: 3.7% for high school graduates with disabilities and 22.0% for high school graduates without disabilities.

The CEDARS K–12 data system can also be linked to the Unemployment Insurance (UI) records of all employed individuals in Washington State, including quarterly wages and an occupational code.[21] The UI records are reported on a quarterly basis and run from 2010 through 2013 on the calendar year. From the UI records, we construct an indicator for being employed more than half time for each of the

[19] The SBCTC contains college enrollment data for school years 2009–10 through 2013–14. However, the last two quarters (January–June) of the 2013–14 school year only contain information on students who were already enrolled (i.e., there are no data on newly enrolled students for these two quarters). We therefore consider college enrollment within six months of a student's expected graduation date.
[20] Unfortunately, reports that document postsecondary attendance trends for students with disabilities using the National Longitudinal Study of Special Education Students (e.g., Wagner, 1992; Wagner et al., 2005) do not disaggregate by public/private college attendance or in-state/out-of-state attendance, so it is difficult to quantify how many college attendees we are missing who attend private or out-of-state colleges.
[21] Note that this database does not include any forms of employment for which individuals do not pay Unemployment Insurance, such as military service or informal work experiences.

two quarters after a student's expected graduation. We then take the maximum of these two indicators to determine whether an individual was employed more than half time in any quarter within the first six months of their expected graduation. Panel E of Table 3 presents employment statistics for students by disability status and illustrates that students with disabilities in the original cohorts are less than half as likely to be employed six months after their expected graduation date as other students (8.0% vs. 16.6%).

4. Analytic Approach

Our analytic approach is to estimate a series of student-level models predicting our measures of intermediate and postsecondary student success. As described in the introduction, these models control for a variety of student characteristics, including baseline measures of performance that are not utilized in many prior studies. However, we view these models as descriptive because our controls may not sufficiently address potential sources of bias.

Specifically, three sources of selection bias could be problematic for the models described in this section. First, students with disabilities may participate in CTE courses or be placed in more general education classes because of unobserved factors that are also correlated with their outcomes. For example, high-ability students with disabilities likely have better postsecondary outcomes regardless of CTE enrollment; if they are more motivated to enroll in CTE courses, then the association between enrollment in CTE courses and postsecondary outcomes will reflect selection bias instead of a causal relationship. Our primary solution to this potential source of bias is to include a rich set of control variables in all models, including baseline measures of performance and other observable student and peer characteristics. This strategy ensures that students are being compared with students with similar prior achievement, who are taking classes with similar types of students, and who are receiving special education for the same disability type.

A second source of selection bias may occur if districts choose to offer more CTE classes or place fewer students with disabilities into general education classrooms because of the population of students they serve (e.g., because students with disabilities in the district are "struggling"). We address this potential source of bias by including district fixed effects in our primary model specifications to compare students within the same district, as well as by controlling for baseline academic performance and other observable student and peer characteristics.

A third source of selection bias may occur if parents choose to send their children to a specific school or district because of the special education services they offer (e.g., more CTE classes specifically targeted to students with disabilities). The role of parents in selecting the schools and districts their children attend could be particularly problematic for students with disabilities. Parents may pay close attention to the special education services offered by different schools and districts before selecting the best schooling environment for their child. If motivated parents are more likely to place their children in schools and districts with more extensive special education services, then parental involvement will confound the estimates from the models described below. Unfortunately, we do not believe there is any way (short of an experiment) to mitigate this source of bias, which is one reason we ultimately view this as a descriptive study.

In addition to the sources of bias described above, we need to consider several data challenges in developing our analytic models. The first challenge is the considerable attrition from the analytic samples from 10th grade to 12th grade, illustrated in Table 1. This attrition appears not to be random (e.g., lower-performing students are more likely to leave the sample) and could be due to students dropping out of school, moving to a private school, or moving to a school outside the state. In many cases, we can distinguish between these competing explanations—for example, if a student drops out of school in the middle of the school year, then this data set includes one of the dropout codes discussed in section 3—but the exit reason cannot be determined for many students who leave between school years. Another challenge is that many of the malleable factors we consider (as well as many of the control variables in Table 2) are time varying. For example, a student may enroll in a CTE course in 10th grade but not in 11th or 12th grade, or a student may attend general education classes for over 80% of the school day in 12th grade but only 40% to 79% of the school day in previous grades.

Our solution to each of these challenges is to define and estimate models separately by grade and to estimate these models only for the subset of students who are still attending Washington State public schools in that grade. This separation means that our estimates in each grade can only be interpreted for the subset of students who remain in Washington State public schools in that grade. Although this approach may seem restrictive, it does make intuitive sense because a malleable factor in 12th grade can only affect students who are still enrolled in school in 12th grade. Furthermore, because we consider persistence as an intermediate outcome (i.e., we investigate which malleable factors in 10th grade predict student persistence into 11th grade), we believe this still paints a complete picture of the potential influences of each malleable factor.

Research question 1: What malleable factors at the high school level are predictive of intermediate outcomes for students with disabilities in Washington State?

We first consider predictors of student unexcused absences, one of the intermediate outcomes described in Section 3. For each student in our analytic sample in grade *g*, we observe the number of unexcused absences ABS_g. We model this intermediate outcome as a function of student control variables in grade *g*, $\mathbf{X}_g$, and malleable factors in grade *g*, $\mathbf{MALL}_g$.

$$ABS_g = \beta_0^{\,g} + \beta_1^{\,g^T} \mathbf{X}_g + \beta_2^{\,g^T} \mathbf{MALL}_g + \varepsilon^{\beta^g} \qquad (1)$$

The coefficients of interest are elements of the vector $\beta_2^{\,g}$ associated with the malleable factors in grade *g*. The coefficient on CTE enrollment can be interpreted as the expected change in the number of unexcused absences associated with CTE enrollment in grade *g*, conditional on the controls in $\mathbf{X}_g$ as well as other malleable factors. Likewise, the coefficients on the indicators of inclusion can be interpreted as the expected change in unexcused absences associated with each level of inclusion in grade *g*, all else equal.

We next consider predictors of student performance on 10th-grade tests. We model each student's score in subject *s*, $TEST_{10,s}$, as a function of student control variables in 10th grade, $\mathbf{X_{10}}$, malleable factors in 10th grade, $\mathbf{MALL_{10}}$, and in some specifications, student absences in 10th grade, ABS_{10}:

$$TEST_{10,s} = \alpha_0 + \alpha_1^T \mathbf{X_{10}} + \alpha_2^T \mathbf{MALL_{10}} + \alpha_3 ABS_{10} + \varepsilon^{\alpha} \qquad (2)$$

The first group of coefficients of interest in model 2 are the elements of α_2 associated with the malleable factors in 10th grade. The second group is the coefficient of interest is α_3, which represents the expected change in student test performance in subject *s* associated with an additional unexcused absence that year. Recall that ABS_{10} was the outcome variable in model 1, and it represents the first mediator in our analysis; that is, the effect of malleable factors in grade 10, $\mathbf{MALL_{10}}$, on student performance in subject *s* in Grade 10, $TEST_{10,s}$, may be mediated by their effect on student absences in Grade 10, ABS_{10}. We will discuss our approach for investigating this potential mediator in some detail when we address research question 3.

The final set of intermediate outcomes we consider are student persistence and graduation. We model the probability that a student persists from grade *g* to grade *g*+1, PER_g, as a function of student control variables in grade *g*, $\mathbf{X_g}$, malleable factors in grade *g*, $\mathbf{MALL_g}$, and (in some specifications and grades) student absences in grade *g*, ABS_g and student test scores in grade *g*, $\mathbf{TEST_g}$:

$$f\left(\Pr(PER_g = 1)\right) = \gamma_0{}^g + \gamma_1{}^{g^T} \mathbf{X}_g + \gamma_2{}^{g^T} \mathbf{MALL}_g + \gamma_3{}^g ABS_g + \gamma_4{}^{g^T} \mathbf{TEST}_g + \varepsilon^{\gamma^g} \qquad (3)$$

In our primary specification of model 3 (and models 4 and 5), we use the identity function for *f* and estimate these regressions as linear probability models.[22] Thus, the coefficients of the vector γ_2^g represent the expected change in the probability of persisting from grade *g* to grade *g*+1 associated with each malleable factor in grade *g*. We also investigate student absences and test scores as potential mediators between the malleable factors and persistence from Grade 10 to 11 (and absences for persistence from Grade 11 to 12).

We estimate similar models predicting on-time graduation:

$$f\left(\Pr(GR=1)\right)=\lambda_0{}^g+\lambda_1{}^{g^T}\mathbf{X}_g+\lambda_2{}^{g^T}\mathbf{MALL}_g+\lambda_3{}^g ABS_g+\lambda_4{}^{g^T}\mathbf{TEST}_g+\lambda_5{}^g PER_g+\varepsilon^{\lambda^g} \quad (4)$$

Although the outcomes of models 3 and 4 are different, the interpretation of the coefficients is very similar: the expected change in the probability of *graduating* associated with each variable in grade *g*, conditional on the controls in $\mathbf{X_g}$ as well as other malleable factors. We estimate these models separately by each grade *g* so malleable factors in each grade can be considered as predictors of on-time graduation, and so that grade progression from grade *g* to grade *g*+1 can be considered as a potential mediator in this relationship.

Research question 2: What malleable factors are predictive of the postsecondary success (college enrollment and employment) of students with disabilities?

We use our measures of postsecondary success as outcome variables in models that address our final two research questions (2 and 3). The grade-specific models predicting each postsecondary outcome *PS* (college enrollment or graduation) are similar to model 4:

$$f\left(\Pr(PS=1)\right)=\rho_0{}^g+\rho_1{}^{g^T}\mathbf{X}_g+\rho_2{}^{g^T}\mathbf{MALL}_g+\rho_3{}^g ABS_g+\rho_4{}^{g^T}\mathbf{TEST}_g+\rho_5{}^g PER_g+\rho_6{}^g GR_g+\varepsilon^{\rho^g}$$

(5)

[22] We also estimate these models as logistic regressions, and the results are qualitatively similar.

As before, the interpretation of these coefficients is similar (i.e., the expected change in the probability of each postsecondary outcome associated with each variable in grade *g*, all else equal). Depending on the grade level we consider, student absences, test scores, grade persistence, and on-time graduation can all be considered as potential mediators in the relationships between the malleable factors as these postsecondary outcomes.

Research question 3: Which intermediate outcomes may mediate the relationship between these malleable factors and measures of postsecondary success?

To illustrate our approach to investigating potential mediators, we describe in detail our investigation of student absences in Grade 10 as a potential mediator between malleable factors in Grade 10 and student performance in subject *s* in Grade 10. In addition to model 1, we estimate a variant of model 1 that does *not* include student absences as a predictor variable:

$$TEST_{10,s} = \alpha_0^{*} + \alpha_1^{*T}\mathbf{X_{10}} + \alpha_2^{*T}\mathbf{MALL_{10}} + \varepsilon^{\alpha^{*}} \qquad (7)$$

The coefficients of the vector α_2^{*} represent the expected change in student test performance in subject *s* associated with each malleable factor, all else equal but *not* controlling for student absences in Grade 10. We use these estimates, along with the estimates from models 1 and 2, to identify potential mediated relationships. We opt for this highly descriptive approach rather than a more formal mediation analysis (e.g., Baron & Kenny, 1986) because we do not believe that the counterfactual assumptions that justify this approach (e.g., no confounding) hold in our application. However, our goal is to *identify* potential mediators rather than quantify potential direct and indirect effects, and we believe that the more general approach above is sufficient to identify potential mediators that are worthy of further consideration.

5. Results

Our preferred specification for each model includes district fixed effects (i.e., in which students are compared with other students within the same district). We focus on this specification for two reasons. First, given disparities in college attendance and employment rates across different geographical areas of Washington State (e.g., Washington Higher Education Coordinating Board, 2012), we believe it is important to make comparisons between students who have similar geographical access to these postsecondary options. Second, although models with school fixed effects have the additional advantage of controlling for school-level factors that may influence student outcomes, they make comparisons exclusively between students within the same school, which may not be the relevant comparison for policy purposes. In particular, we believe that interventions related to the malleable factors considered in this study would likely be done at the school level, so we want to ensure that our primary results reflect cross-school as well as within-school relationships. We consider both models without district fixed effects and models with school fixed effects later in this section.

Tables 4–6 present estimates from our preferred specifications of the models described in Section 4. Each table of results focuses on malleable factors within a specific grade level: Tenth-grade malleable factors are in Table 4, 11th-grade malleable factors are in Table 5, and 12th-grade malleable factors are in Table 6. Each table is intended to address all three research questions for the given grade level. Specifically, the first set of horizontal panels presents models predicting intermediate and transition outcomes (absences, test scores, grade progression, and graduation), and thus addresses research question 1. The second set of panels presents models predicting postsecondary outcomes (college enrollment and employments), addressing research question 2. Different specifications within each panel both do and do not control for different intermediate and transition outcomes that are potential mediators; the differences between the estimates in these columns address research question 3.

Table 4 presents estimates of the relationships between CTE enrollment and inclusion in 10th grade and intermediate and postsecondary outcomes for students with disabilities. The first broad conclusion from this table is that CTE enrollment in 10th grade is not consistently predictive any of the outcomes of interest. In contrast, students with disabilities who are included in mostly general education courses (80% to 100%) in 10th grade score considerably higher on the 10th-grade reading test (by approximately 9% of a standard deviation), are more likely to graduate on time (by approximately 3.5 percentage points), and are more likely to enroll in college in the six months after their expected graduation year (by approximately 3.5 points) than students with disabilities who spend less time in general education courses but are similar in other observable ways.

In most cases, the inclusion results are consistent whether or not we control for CTE enrollment or potential mediators. The one exception is the relationship with on-time graduation; the relationship between inclusion and the probability of on-time graduation is considerably smaller when we control for potential mediators, including absences, 10th-grade reading score, and progression to 11th grade. Given that inclusion is significantly associated only with 10th-grade reading score, this provides descriptive evidence that the positive relationship between inclusion and the probability of on-time graduation is mediated by 10th-grade reading performance (i.e., students with disabilities who spend more time in general education courses are more likely to graduate on time in part *because* of their higher proficiency in reading).

Table 5 presents estimates of the relationships between CTE enrollment and inclusion in 11th grade and subsequent outcomes. As in 10th grade, there is little evidence relating CTE enrollment in 11th grade to these outcomes, though there is tenuous evidence connected CTE enrollment in 11th grade to higher rates of grade progression and lower rates of college enrollment. Also similar to the results from 10th grade, students with disabilities who spend more time in general education courses in 11th grade are more likely to graduate on time, enroll in college, and find employment than students with disabilities who spend less time in general education courses, all else equal. Given that there is no 11th-grade test, we are unable to test whether the relationship between inclusion in 11th grade and on-time graduation is mediated by student performance. The magnitudes of the relationships between inclusion and these outcomes are even larger in 11th grade than they were in 10th grade.

In **Table 6**, we turn to the relationships between CTE enrollment and inclusion in 12th grade and intermediate and postsecondary outcomes. At this grade level, we find consistent evidence that CTE enrollment is positively predictive of on-time graduation; specifically, students with disabilities who participate in CTE courses in 12th grade are approximately 3-4 percentage points more likely to graduate at the end of the year than students with disabilities who do not participate, all else equal. However, CTE enrollment in 12^{th} grade does not predict employment, and there is some evidence that CTE enrollment in 12^{th} grade is positively predictive of absences and negatively predictive of college enrollment, though the relationship with college enrollment does not hold when we control for level of inclusion. Overall, the relationships between CTE enrollment in 12th grade and intermediate and postsecondary outcomes for students with disabilities are inconsistent.

In contrast to CTE enrollment in 12^{th} grade, we find strong evidence that inclusion in 12^{th} grade is positively predictive of intermediate and postsecondary outcomes; students with disabilities who spend 80-100% of the school day in general education classes have fewer absences and are more likely to graduate on time, enroll in college, and find employment than students with disabilities who spend less time in general education classrooms, all else equal.[23] The relationships between inclusion and the postsecondary outcomes (college enrollment and employment) appear to be partially, but not entirely, mediated by absences and on-time graduation.

Extensions and Robustness Checks

[23] These results are even stronger when we consider employment and college attendance within 18 months of the expected graduation date of the first cohort of students; results available from authors upon request.

We pursue four sets of extensions and robustness checks to the results discussed above. First, we estimate all models reported in Tables 4–6 both without district fixed effects and with school fixed effects to check the robustness of our findings to these different modeling decisions. The broad conclusion from this exploration is that most findings are robust to different modeling decisions; for example, the consistent positive relationships between inclusion and measures of success for students with disabilities hold across all of these additional model specifications.

As a second extension, we follow Wagner et al. (2016) and consider whether students with disabilities are enrolled in a "concentration" of CTE courses in high school. Like Wagner et al. (2016), we define concentration as taking four or more credits of CTE courses in high school. Rates of concentration are quite similar between both studies, with 35.5% of students with disabilities in our sample taking a concentration of CTE courses during high school, compared to 36.8% in Wagner et al. (2016). We also create an analogous measure for inclusion by counting the number of years a student spends in the highest level of inclusion (80%-100% general education) between grades 10 through 12**.**

Table 7 presents results from models that use the concentration variables described above as predictors of the same outcomes presented in Table 6.[24] We find consistent evidence that students with disabilities who are enrolled in a concentration of CTE courses have fewer absences (by about 16% of a standard deviation), are more likely to graduate on-time (by about 2-3 percentage points), and are more likely to be employed after their expected graduation date (by about 2 percentage points) than students with disabilities who are similar in other observable ways but who are not enrolled in a concentration of CTE courses. This replicates a subset of the findings in Wagner et al. (2016), and supports this prior evidence that a concentration of CTE courses is predictive of postsecondary outcomes for students with disabilities. The results for inclusion further support the relationships described in Tables 4-6;

[24] We limit this analysis to students who were receiving special education services in all three grades because the inclusion variables are only observable for students in special education.

specifically, students who are in the highest level of inclusion in grades 10-12 are 7-8 percentage points more likely to graduate on time, 8 percentage points more likely to enroll in college, and 5 percentage points more likely to be employed after high school than students who are not in the highest level of inclusion in any of these grades, all else equal.

As discussed in the previous section, one concern in interpreting these findings is that they may be driven by selection bias—i.e., students who take more CTE courses or who are enrolled in higher levels of inclusion are already more likely to experience higher outcomes—rather than by the effect of CTE enrollment or inclusion. Our analytic approach attempts to account for selection bias by controlling for district fixed effects, student demographics, student disability type, prior test scores, and peer effects in estimating these effects. To explore the influence of these various controls on our findings, **Table 8** replicates a subset of the models from Table 7 but with varying levels of controls: Column 1 does not include any controls; Column 2 adds district and year fixed effects; Column 3 adds student demographic controls; Column 4 adds controls for student disability type; Column 5 adds controls for prior test scores; and Column 6 adds controls for peer effects. The changes in the estimated coefficients across columns illustrate the sensitivity of our estimates to the inclusion of different controls in our analytic models.

We draw two broad conclusions from this exercise. First, the relationships between inclusion and postsecondary outcomes are positive in all specifications, but become considerably smaller in magnitude when we control for student prior test scores (column 5) and peer effects (column 6). In particular, estimates from models that do not include these controls are 51 to 116 percent larger when predicting college enrollment and 23 to 47 percent larger when predicting postsecondary employment. This is consistent with the lower-performing students being systematically sorted into lower levels of inclusion; we illustrate this sorting in **Figure 1**, which plots the distribution of 8th grade reading test scores for students with disabilities in each level of inclusion in 12th grade. This illustrates the importance of controlling for prior year test scores in any comparison between levels of inclusion. The controls for peer effects are perhaps more debatable—after all, the exposure to higher-performing peers may be one mechanism through which inclusion improves outcomes for students with disabilities—but the fact that the relationship between inclusion and postsecondary outcomes is still large and positive even after including these controls supports our broad conclusion about the benefits of inclusion for students with disabilities.

The second broad conclusion is that the relationships between CTE concentration and postsecondary outcomes are largely robust to model specification, and in some cases (e.g., predicting employment), the relationships are even larger after we include all the controls in the model. Importantly, the relationships appear to change the most when we include controls for district fixed effects (column 2), which suggests that studies that make comparisons across districts may understate the importance of CTE participation for students with disabilities. That said, our overall conclusion is that nonrandom selection bias is less of a concern for CTE enrollment than inclusion.

Our final extension investigates whether the findings above are consistent for students receiving special education for different disabilities. We find considerable heterogeneity in the results by student disability type. To illustrate this heterogeneity, we report estimates from the models summarized in Table 7 for two different subsets of students with disabilities: students receiving special education services for a SLD (**Table 9**); and students receiving special education services for a different disability (**Table 10**). In comparing the results between these tables, we see that the positive relationships between inclusion and postsecondary outcomes are driven primarily by students receiving special education services for a different disability, though there is a positive relationship between inclusion and the probability of college enrollment for students in both categories. Likewise, the positive relationships between CTE concentration and the probability of employment are quite consistent across the two categories.

6. Conclusions

This study uses student longitudinal data to present descriptive evidence on the relationships between CTE enrollment, inclusion, and intermediate and postsecondary outcomes for students with disabilities. We use these detailed administrative data to control for several characteristics, including baseline academic performance and district fixed effects. It is important to emphasize that there are good reasons to believe that these descriptive relationships may not represent *causal* relationships (i.e., it may not be true that inclusion *causes* students with disabilities to experience better outcomes), although the results presented in the paper are descriptively true (e.g., students with disabilities who spend more time in general education classrooms experience consistently better outcomes than students with disabilities who spend less time, all else equal).

That said, we believe that our models contain sufficient controls (particularly for baseline achievement and peer effects)—and that the results from these models are sufficiently robust to different extensions and robustness checks—to warrant some preliminary conclusions. As a prime example, the relationships between inclusion and subsequent outcomes are so consistent, both within this paper and with prior research (e.g., Wagner, 1991), that we interpret these relationships as strong evidence that students with disabilities receive benefits from greater participation in general education classrooms that impact their future outcomes. The policy implications of this conclusion are straightforward and are consistent with the foundation of special education law guaranteeing services for students with disabilities “in the least restrictive environment possible” (Individuals with Disabilities Education Act (IDEA), 20 U.S.C. §§ 1401 et seq. (2012)).

The results relating CTE enrollment to these outcomes are not consistent when participation is captured by whether a student is enrolled in a CTE course in a particular grade. In contrast, we find that the concentration of CTE enrollment across high school grades is positively predictive of intermediate and long-term outcomes for students with disabilities, which closely matches the findings from Wagner et al. (2016). Both this extension and prior research on the importance of specific aspects of CTE programs (Gottfried et al., 2016; Plasman & Gottfried, 2016) suggest that more nuanced research considering particular aspects of CTE participation, particularly for students with disabilities, could be a promising line of future work.

We close by discussing two broader implications of this study. The first is that the field would benefit from more research that leverages new state-level administrative data systems, like the one used in this study, to perform large-scale studies on students with disabilities. It is surprising that, given the large administrative databases being developed and used throughout the country, this study is the first to use a statewide longitudinal database to link course taking and inclusion in high school to postsecondary outcomes for students with disabilities. Similar research in other states could provide important information about the extent to which these results hold across different educational settings.

Finally, the reality that even large, carefully controlled studies like this may not permit causal conclusions motivates the need for more large-scale experimental research in special education. Much has been written about the logistical and potential ethical concerns about experimental designs in special education research (e.g., Mertens & McLaughlin, 2004), and it is clear that the individualized nature of special education services makes research interventions particularly challenging. On the other hand, it is equally clear that the field of special education could benefit tremendously from experimental evidence that builds on rigorous descriptive analyses like this study. We therefore view this analysis as an important first step toward developing this evidence base, but we urge further research that can provide more plausibly causal evidence about what works for students with disabilities.

References

Affleck, J. Q., Edgar, E., Levine, P., & Kortering, L. (1990). Postschool status of students classified as mildly mentally retarded, learning disabled, or nonhandicapped: Does it get better with time? *Education & Training in Mental Retardation, 25*(4), 315–324.

Allensworth, E. M., & Easton, J. Q. (2007). What matters for staying on-track and graduating in Chicago Public High Schools: A close look at course grades, failures, and attendance in the freshman year. Research report. Chicago, IL: Consortium on Chicago School Research.

Baer, R. M., et al. (2003). A collaborative follow up study on transition service utilization and post-school outcomes. *Career Development for Exceptional Individuals, 26*(1), 7–25.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182.

Benz, M. R., Lindstrom, L., & Yovanoff, P. (2000). Improving graduation and employment outcomes of students with disabilities: Predictive factors and student perspectives. *Exceptional Children, 66*(4), 509–529.

Carl D. Perkins Career and Technical Education Improvement Act, Pub. L. No. 109-270 (2006).

Dortch, C. (2012). *Carl D. Perkins Career and Technical Education Act of 2006: Background and Performance*. Congressional Research Service 7-5700. Retrieved from https://fas.org/sgp/crs/misc/R42863.pdf

Education for All Handicapped Children Act, Pub. L. No. 94-142) (1975).

Gersten, R., Fuchs L. S., Williams, J. P., & Baker, S. (2001). Teaching reading comprehension strategies to students with learning disabilities: A review of research. *Review of Educational Research, 71*(2), 279–320.

Goldberger, A. S., & Cain, G. G. (1982). The causal analysis of cognitive outcomes in the Coleman, Hoffer and Kilgore report. *Sociology of Education, 55*(2), 103–122.

Gottfried, M. A. (2009). Excused versus unexcused: How student absences in elementary school affect academic achievement. *Educational Evaluation and Policy Analysis, 31*(4), 392–415.

Gottfried, M. A., Bozick, R., Rose, E., & Moore, R. (2016). Does career and technical education strengthen the STEM pipeline? Comparing students with and without disabilities. *Journal of Disability Policy Studies, 26*(4), 232–244.

Haber, M.G., Mazzotti, V.L., Mustian, A.L., Rowe, D.A., Bartholomew, A.L., Test, D.W. and Fowler, C.H. (2016). What works, when, for whom, and with whom: A meta-analytic review of predictors of postsecondary success for students with disabilities. *Review of Educational Research*, 86(1), pp.123-162.

Harvey, M. W. (2002). Comparison of postsecondary transitional outcomes between students with and without disabilities by secondary vocational education participation: Findings from the national education longitudinal study. *Career Development for Exceptional Individuals, 25*(2), 99–122.

Hasazi, S. B., Gordon, L. R., & Roe, C. A. (1985). Factors associated with the employment status of handicapped youth exiting high school from 1979 to 1983. *Exceptional Children, 51*96), 455–477.

Heal, L. W., & Rusch F. R. (1995). Predicting employment for students who leave special education high school programs. *Exceptional Children, 1*(5), 472–487.

Heckman, J.J., Stixrud, J. and Urzua, S., 2006. The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, 24(3), pp. 411-482.

Individuals with Disabilities Education Improvement Act of 2004, 20 U.S.C. §612 (2004).

Karpinski, M. J., Neubert, D. A., & Graham, S. A. (1992). Follow-along study of postsecondary outcomes for graduates and dropouts with mild disabilities in a rural setting. *Journal of Learning Disabilities, 25*(6), 376–385.

Mazzotti, V. L., Rowe, D. R., Sinclair, J., Poppen, M., Woods, W. E., & Shearer, M. L. (2016, November). Predictors of post-school success: A systematic review of NLTS2 Secondary analyses. *Career Development and Transition for Exceptional Individuals*, 39(4), 196–215.

Mertens, D. M., & McLaughlin, J. A. (2004). *Research and evaluation methods in special education*. Thousand Oaks, CA: Corwin Press.

Mithaug, D. E., Horiuchi, C. N., & Fanning, P. N. (1985). A report on the Colorado statewide follow-up survey of special education students. *Exceptional Children, 51*(5), 397–404.

Morgan, P. L., Frisco, M. L., Farkas, G., & Hibel, J. (2010). A propensity score matching analysis of the effects of special education services. *The Journal of Special Education, 43*(4), 236–254.

Murray, C., Goldstein, D. E., Nourse, S., & Edgar, E. (2000). The postsecondary school attendance and completion rates of high school graduates with learning disabilities. *Learning Disabilities Research & Practice, 15*(3), 119–127.

Newman, L., Wagner, M., Cameto, R., Knokey, A.-M., & Shaver, D. (2010). *Comparisons across time of the outcomes of youth with disabilities up to 4 years after high school. A report of findings from the National Longitudinal Transition Study (NLTS) and the National Longitudinal Transition Study-2 (NLTS2)* (NCSER 2010-3008). Washington, DC: National Center for Special Education Research.

Plasman, J. S., & Gottfried, M. A. (2016). Applied STEM coursework, high school dropout rates, and students with learning disabilities. *Educational Policy.* doi:0895904816673738.

Rabren, K., Dunn, C., & Chambers, C. (2002). Predictors of post-high school employment among young adults with disabilities. *Career Development for Exceptional Individuals, 25*(1), 25–40.

Rea, P. J., McLaughlin, V. L., & Walther-Thomas, C. (2002). Outcomes for students with learning disabilities in inclusive and pullout programs. *Exceptional Children, 68*(2), 203–223.

Rose, H. (2006). Do gains in test scores explain labor market outcomes?. *Economics of Education Review,* 25(4), pp.430-446.

Sitlington, P. L., & Frank, A. R. (1990). Are adolescents with learning disabilities successfully crossing the bridge into adult life? *Learning Disability Quarterly, 13*(2), 97–111.

Test, D. W., Mazzotti, V. L., Mustian, A. L., Fowler, C. H., Kortering, L., & Kohler, P. (2009). Evidence-based secondary transition predictors for improving postschool outcomes for students with disabilities. *Career Development for Exceptional Individuals, 32*(3), 160–181.

National Center for Education Statistics, U.S. Department of Education. (2016). *Digest of Education Statistics, 51st edition.*

Wagner, M. (1991). *Youth with disabilities: How are they doing? The first comprehensive report from the National Longitudinal Transition Study of Special Education Students*. Menlo Park, CA: SRI International. Retrieved from http://files.eric.ed.gov/fulltext/ED341228.pdf

Wagner, M. (1992). *What happens next? Trends in postschool outcomes of youth with disabilities. The second comprehensive report from the National Longitudinal Transition Study of Special Education Students*. Menlo Park, CA: SRI International. Retrieved from http://files.eric.ed.gov/fulltext/ED356603.pdf

Wagner, M. (1993). *Beyond the report card: The multiple dimensions of secondary school performance of students with disabilities. A report from the National Longitudinal Transition Study of Special Education Students*. Menlo Park, CA: SRI International. Retrieved from http://files.eric.ed.gov/fulltext/ED365088.pdf

Wagner, M., Newman, L., Cameto, R., Garza, N., & Levine, P. (2005). *After high school: A first look at the postschool experiences of youth with disabilities. A report from the National Longitudinal Transition Study-2 (NLTS2).* Menlo Park, CA: SRI International.

Wagner, M., Newman, L., Cameto, R., Levine, P. & Garza, N. (2006). *An overview of findings from wave 2 of the National Longitudinal Transition Study-2 (NLTS2)* (NCSER 2006-3004). Washington, DC: National Center for Special Education Research, Institute of Education Sciences, U.S. Department of Education.

Wagner, M. M., Newman, L. A., & Javitz, H. S. (2016). The benefits of high school career and technical education (CTE) for youth with learning disabilities. *Journal of Learning Disabilities*, 49(6), 658-670.

Washington Higher Education Coordinating Board. (2012). *Key facts about higher education in Washington*. Olympia, WA: Author. Retrieved from http://wsac.wa.gov/sites/default/files/KeyFacts2012.pdf

Table 1. Student Counts by Cohort, Grade, and Disability Type

	Cohort 1			Cohort 2			Unique Students
	Grade 10	Grade 11	Grade 12	Grade 10	Grade 11	Grade 12	
	2009–10	2010–11	2011–12	2010–11	2011–12	2012–13	
No disability reported (non–special education)	66,903	57,808	53,738	67,532	59,842	54,760	134,435
Specific learning disability	4,021	3,226	2,750	3,923	3,327	2,787	7,944
Health impairment	2,008	1,640	1,355	2,179	1,856	1,536	4,187
Autism	492	462	408	512	467	403	1,004
Emotional/behavioral disability	423	271	200	416	289	197	839
Intellectual disability	379	342	294	406	366	318	785
Multiple disabilities	203	191	163	195	180	144	398
Communication disorders	193	285	263	316	258	222	509
Hearing impairment	50	40	34	57	44	38	107
Orthopedic impairment	34	28	26	25	24	19	59
Traumatic brain injury	35	28	29	26	22	21	61
Deafness	29	21	20	34	26	24	63
Visual impairment	25	24	19	22	18	18	47
Total	74,795	64,366	59,299	75,643	66,719	60,487	150,438
Total With Disabilities	7,892	6,558	5,561	8,111	6,877	5,727	16,003

Note. Sample sizes suppressed for disability categories (developmental delays and deaf-blindness) with fewer than 10 students in a year. Disability type in "Unique students" column is from student's first year in the analytic sample.

Table 2. Student Covariates Summary Statistics

	Non–SPED	SPED		
		All	SLD	non-SLD
Panel A: Demographics				
Proportion female	0.513	0.347	0.391	0.304
Proportion underrepresented minority	0.202	0.27	0.343	0.2
Proportion limited English proficiency	0.15	0.142	0.196	0.089
Proportion receiving free or reduced-priced lunch	0.359	0.544	0.609	0.482
Panel B: Baseline test scores				
Average standardized eighth-grade math score	0.220	-1.183	-1.259	-1.092
Average standardized eighth-grade reading score	0.213	-1.218	-1.286	-1.137
Average standardized eighth-grade science score	0.217	-1.102	-1.173	-1.017
Panel C: Participation in CTE				
Proportion participating in CTE	0.671	0.678	0.732	0.625
Panel D: Extent of Inclusion				
Proportion 80% to 100% general education	0	0.461	0.522	0.398
Proportion 40% to 79% general education	0	0.413	0.441	0.383
Proportion 0% to 39% general education	0	0.113	0.032	0.197
Proportion other school setting	0	0.013	0.005	0.021

Note. CTE = career and technical education. SLD = specific learning disability. SPED = special education

Table 3. Student Outcome Summary Statistics

	non-SPED	SPED		
		All	SLD	non-SLD
Panel A: Student absences				
Average number unexcused absences in 10th grade	1.033	1.782	1.859	1.706
Average number unexcused absences in 11th grade	2.054	3.524	3.875	3.191
Average number unexcused absences in 12th grade	3.877	5.805	6.71	4.935
Panel B: Student test performance				
Average standardized 10th-grade reading test score	0.284	-0.98	-1.028	-0.924
Average standardized 10th-grade math test score	0.351	-0.93	-0.974	-0.875
Average standardized 10th-grade Algebra EOC score	0.104	-0.379	-0.382	-0.374
Average standardized 10th-grade Geometry EOC score	0.053	-0.473	-0.621	-0.301
Panel C: Student grade progression and graduation				
Proportion 10th graders progressing to 11th grade	0.975	0.960	0.959	0.961
Proportion 11th graders progressing to 12th grade	0.976	0.939	0.955	0.925
Proportion 12th graders graduating on time	0.920	0.714	0.807	0.625
Proportion 10th-grade cohort graduating on time	0.838	0.596	0.678	0.515
Five-year graduation rate for 12th graders	0.948	0.820	0.894	0.746
Five-year graduation rate for 10th-grade cohort	0.876	0.702	0.765	0.638
Panel D: College attendance within one year of expected graduation date				
Proportion on-time graduates in two-year college	0.221	0.193	0.186	0.202
Proportion on-time graduates in four-year college	0.220	0.037	0.027	0.050
Proportion of original cohort in two-year college	0.199	0.129	0.137	0.122
Proportion of original cohort in four-year college	0.185	0.022	0.019	0.026
Panel E: Employment within six months of expected graduation date				
Proportion on-time graduates employed at least half time	0.179	0.110	0.126	0.089
Proportion of original cohort employed at least half time	0.166	0.080	0.105	0.055

Note. CTE = career and technical education. EOC = end-of-course exam. SLD = specific learning disability. SPED = special education

Table 4. Tenth-Grade CTE enrollment and Inclusion Models

Panel A: Predicting number of absences in 10th grade						
Enrolled in a CTE course	-0.022		-0.023			
	(0.020)		(0.022)			
80%-100% general education		-0.017	-0.018			
		(0.021)	(0.021)			
Number students	11424	9804	9804			
Panel B: Predicting 10th grade reading score						
Enrolled in a CTE course	-0.005	-0.005			-0.008	-0.008
	(0.014)	(0.014)			(0.015)	(0.015)
80%-100% general education			0.089***	0.089***	0.089***	0.088***
			(0.016)	(0.016)	(0.016)	(0.016)
Student absences		-0.020*		-0.021**		-0.021**
		(0.008)		(0.008)		(0.008)
Number students	10317	10317	8844	8844	8844	8844
Panel C: Predicting progression to 11th grade						
Enrolled in a CTE course	-0.002	-0.007+			-0.004	-0.008+
	(0.005)	(0.004)			(0.005)	(0.004)
80%-100% general education			0.002	-0.001	0.002	-0.001
			(0.005)	(0.005)	(0.005)	(0.005)
Student absences		-0.032***		-0.026***		-0.026***
		(0.007)		(0.007)		(0.007)
Student 10th grade reading score		0.010**		0.012***		0.012***
		(0.003)		(0.003)		(0.003)
Number students	11165	10138	9565	8681	9565	8681
Panel D: Predicting on-time graduation						
Enrolled in a CTE course	0.005	0.002			0.006	0.004
	(0.010)	(0.010)			(0.012)	(0.011)
80%-100% general education			0.034**	0.019	0.034**	0.019
			(0.012)	(0.012)	(0.012)	(0.012)
Student absences		-0.040***		-0.044***		-0.044***
		(0.009)		(0.010)		(0.010)
Student 10th grade reading score		0.080***		0.082***		0.082***
		(0.008)		(0.009)		(0.009)
Student progression to 11th grade		0.519***		0.523***		0.524***
		(0.024)		(0.027)		(0.027)
Number students	10612	9675	9092	8282	9092	8282
Panel E: Predicting enrollment in college six months after expected graduation year						
Enrolled in a CTE course	-0.008	-0.009			-0.013	-0.014
	(0.008)	(0.009)			(0.009)	(0.010)
80%-100% general education			0.037***	0.035**	0.037***	0.034**
			(0.010)	(0.011)	(0.010)	(0.011)
Student absences		-0.009*		-0.009*		-0.010*
		(0.004)		(0.005)		(0.005)
Student 10th grade reading score		0.023***		0.025***		0.024***
		(0.007)		(0.007)		(0.007)
On-time graduation		0.137***		0.132***		0.132***
		(0.008)		(0.009)		(0.008)
Number students	10612	9675	9092	8282	9092	8282
Panel F: Predicting employment in six months after expected graduation year						
Enrolled in a CTE course	0.006	0.007			0.008	0.007
	(0.006)	(0.006)			(0.006)	(0.007)
80%-100% general education			0.015*	0.013+	0.016*	0.014+
			(0.008)	(0.008)	(0.008)	(0.008)
Student absences		-0.005		-0.004		-0.004
		(0.004)		(0.004)		(0.004)
Student 10th grade reading score		0.007		0.009+		0.010+
		(0.005)		(0.005)		(0.005)
On-time graduation		0.052***		0.053***		0.053***
		(0.007)		(0.007)		(0.007)
Number students	10612	9675	9092	8282	9092	8282

Note. P-values from two-sided t-test : +p<0.1, *p<0.05, **p<0.01, ***p<0.001. All models control for lagged absences, race/ethnicity, gender, bilingual status, housing status, migrant status, English Language Learning status, highly capable/gifted status, home school status, a cubic polynomial of 8th grade WASL scores, disability type, number of years diagnosed with a disability since 7th grade, peer effects, and include a district fixed effect. Student progression to 11th grade omitted as mediator in Panels E and F because of space restrictions. Standard errors are clustered at the school level.

Table 5. Eleventh-Grade CTE enrollment and Inclusion Models

Panel A: Predicting number of absences in 11th grade						
Enrolled in a CTE course	-0.047		-0.049			
	(0.033)		(0.035)			
80%-100% general education		-0.037	-0.040			
		(0.037)	(0.037)			
Number students	10080	7773	7773			
Panel B: Predicting progression to 12th grade						
Enrolled in a CTE course	0.013*	0.012+			0.013*	0.012+
	(0.006)	(0.006)			(0.007)	(0.007)
80%-100% general education			0.013+	0.013+	0.014*	0.014+
			(0.007)	(0.007)	(0.007)	(0.007)
Student absences		-0.014***		-0.011**		-0.011**
		(0.004)		(0.004)		(0.004)
Number students	9821	9821	7586	7586	7586	7586
Panel C: Predicting on-time graduation						
Enrolled in a CTE course	0.011	-0.001			0.009	-0.001
	(0.011)	(0.010)			(0.012)	(0.011)
80%-100% general education			0.072***	0.066***	0.073***	0.066***
			(0.014)	(0.012)	(0.014)	(0.012)
Student absences		-0.048***		-0.049***		-0.049***
		(0.004)		(0.005)		(0.005)
Student progression to 12th grade		0.618***		0.642***		0.642***
		(0.017)		(0.018)		(0.018)
Number students	9646	9646	7455	7455	7455	7455
Panel D: Predicting enrollment in college six months after expected graduation year						
Enrolled in a CTE course	-0.021*	-0.023*			-0.018+	-0.020+
	(0.010)	(0.010)			(0.010)	(0.010)
80%-100% general education			0.056***	0.047***	0.055***	0.046***
			(0.011)	(0.011)	(0.011)	(0.011)
Student absences		-0.009**		-0.008*		-0.008*
		(0.003)		(0.004)		(0.004)
Student progression to 12th grade		-0.009		-0.015		-0.014
		(0.012)		(0.014)		(0.014)
On-time graduation		0.134***		0.119***		0.119***
		(0.008)		(0.008)		(0.008)
Number students	9646	9646	7455	7455	7455	7455
Panel F: Predicting employment in six months after expected graduation year						
Enrolled in a CTE course	-0.006	-0.007			-0.006	-0.007
	(0.007)	(0.007)			(0.008)	(0.008)
80%-100% general education			0.035***	0.031**	0.035***	0.031**
			(0.010)	(0.010)	(0.010)	(0.010)
Student absences		-0.003		-0.003		-0.003
		(0.002)		(0.002)		(0.002)
Student progression to 12th grade		0.007		-0.000		-0.000
		(0.009)		(0.011)		(0.011)
On-time graduation		0.056***		0.054***		0.054***
		(0.007)		(0.008)		(0.008)
Number students	9646	9646	7455	7455	7455	7455

Note. P-values from two-sided t-test : +p<0.1, *p<0.05, **p<0.01, ***p<0.001. All models control for lagged absences, race/ethnicity, gender, bilingual status, housing status, migrant status, English Language Learning status, highly capable/gifted status, home school status, a cubic polynomial of 8th grade WASL scores, disability type, number of years diagnosed with a disability since 7th grade, peer effects, and include a district fixed effect. Standard errors are clustered at the school level.

Table 6. Twelfth-Grade CTE enrollment and Inclusion Models

Panel A: Predicting number of absences in 12th grade						
Enrolled in a CTE course	0.101**		0.087*			
	(0.037)		(0.039)			
80%-100% general education		-0.082*	-0.080*			
		(0.040)	(0.040)			
Number students	8178	6509	6509			
Panel B: Predicting on-time graduation						
Enrolled in a CTE course	0.040**	0.045***			0.028+	0.032*
	(0.012)	(0.012)			(0.015)	(0.015)
80%-100% general education			0.065***	0.060***	0.065***	0.061***
			(0.013)	(0.013)	(0.013)	(0.012)
Student absences		-0.051***		-0.051***		-0.051***
		(0.005)		(0.007)		(0.007)
Number students	8060	8054	6424	6421	6424	6421
Panel C: Predicting enrollment in college six months after expected graduation year						
Enrolled in a CTE course	-0.019+	-0.023*			-0.015	-0.017
	(0.011)	(0.011)			(0.013)	(0.013)
80%-100% general education			0.053***	0.045***	0.052***	0.044***
			(0.012)	(0.011)	(0.012)	(0.011)
Student absences		-0.015***		-0.015***		-0.015***
		(0.003)		(0.003)		(0.003)
On-time graduation		0.127***		0.109***		0.110***
		(0.009)		(0.010)		(0.010)
Number students	8060	8054	6424	6421	6424	6421
Panel D: Predicting employment in six months after expected graduation year						
Enrolled in a CTE course	-0.008	-0.010			-0.003	-0.004
	(0.008)	(0.008)			(0.010)	(0.010)
80%-100% general education			0.025**	0.022*	0.025**	0.022*
			(0.009)	(0.009)	(0.009)	(0.009)
Student absences		-0.004		-0.003		-0.003
		(0.003)		(0.003)		(0.003)
On-time graduation		0.052***		0.047***		0.047***
		(0.007)		(0.008)		(0.008)
Number students	8060	8054	6424	6421	6424	6421

Note. P-values from two-sided t-test : +p<0.1, *p<0.05, **p<0.01, ***p<0.001. All models control for lagged absences, race/ethnicity, gender, bilingual status, housing status, migrant status, English Language Learning status, highly capable/gifted status, home school status, a cubic polynomial of 8th grade WASL scores, disability type, number of years diagnosed with a disability since 7th grade, peer effects, and include a district fixed effect. Standard errors are clustered at the school level.

Table 7. CTE & Inclusion Concentration Models

Panel A: Predicting number of absences in 12th grade						
Four or more CTE credits	-0.165***		-0.164***			
	(0.048)		(0.048)			
80%-100% general education: 1 Year		-0.026	-0.020			
		(0.066)	(0.067)			
80%-100% general education: 2 Years		-0.026	-0.020			
		(0.062)	(0.062)			
80%-100% general education: 3 Years		-0.078	-0.072			
		(0.053)	(0.053)			
Number students	4486	4486	4486			
Panel B: Predicting on-time graduation						
Four or more CTE credits	0.034*	0.024+			0.033*	0.023+
	(0.013)	(0.013)			(0.013)	(0.013)
80%-100% general education: 1 Year			0.013	0.012	0.012	0.011
			(0.021)	(0.020)	(0.021)	(0.020)
80%-100% general education: 2 Years			0.055**	0.054**	0.054**	0.053**
			(0.019)	(0.019)	(0.019)	(0.019)
80%-100% general education: 3 Years			0.077***	0.072***	0.075***	0.071***
			(0.019)	(0.019)	(0.019)	(0.019)
Student absences		-0.057***		-0.057***		-0.057***
		(0.008)		(0.008)		(0.008)
Number students	4445	4444	4445	4444	4445	4444
Panel C: Predicting enrollment in college in six months after expected graduation year						
Four or more CTE credits	-0.001	-0.007			-0.003	-0.008
	(0.015)	(0.015)			(0.015)	(0.015)
80%-100% general education: 1 Year			0.027	0.026	0.028	0.026
			(0.017)	(0.017)	(0.017)	(0.017)
80%-100% general education: 2 Years			0.033+	0.027	0.033+	0.027
			(0.018)	(0.018)	(0.018)	(0.018)
80%-100% general education: 3 Years			0.085***	0.076***	0.085***	0.077***
			(0.018)	(0.018)	(0.018)	(0.018)
Student absences		-0.012**		-0.012**		-0.012**
		(0.004)		(0.004)		(0.004)
On-time graduation		0.101***		0.096***		0.096***
		(0.013)		(0.013)		(0.013)
Number students	4445	4444	4445	4444	4445	4444
Panel D: Predicting employment in six months after expected graduation year						
Four or more CTE credits	0.025*	0.022+			0.024*	0.022+
	(0.012)	(0.012)			(0.012)	(0.012)
80%-100% general education: 1 Year			0.006	0.005	0.005	0.004
			(0.014)	(0.014)	(0.014)	(0.014)
80%-100% general education: 2 Years			0.051***	0.048**	0.050**	0.048**
			(0.015)	(0.015)	(0.015)	(0.015)
80%-100% general education: 3 Years			0.052**	0.047**	0.051**	0.047**
			(0.016)	(0.016)	(0.016)	(0.016)
Student absences		-0.004		-0.004		-0.004
		(0.004)		(0.004)		(0.004)
On-time graduation		0.054***		0.051***		0.050***
		(0.011)		(0.011)		(0.011)
Number students	4445	4444	4445	4444	4445	4444

NOTE : p-values from two-sided t-test : +p<0.1, *p<0.05, **p<0.01, ***p<0.001. All models control for lagged absences, race/ethnicity, gender, bilingual status, housing status, migrant status, English Language Learning status, highly capable/gifted status, home school status, a cubic polynomial of 8th grade WASL scores, disability type, number of years diagnosed with a disability since 7th grade, peer effects, and include a district fixed effect. Standard errors are clustered at the school level.

Table 8. CTE and Inclusion Concentration Models – Robustness Check

Panel A: Predicting number of absences in 12th grade						
Four or more CTE credits	-0.159**	-0.231***	-0.152**	-0.158**	-0.159**	-0.164***
	(0.055)	(0.050)	(0.048)	(0.048)	(0.049)	(0.048)
80%-100% general education: 1 Year	0.027	-0.047	-0.024	-0.037	-0.030	-0.020
	(0.086)	(0.070)	(0.064)	(0.062)	(0.064)	(0.067)
80%-100% general education: 2 Years	-0.024	-0.095	-0.050	-0.070	-0.051	-0.020
	(0.066)	(0.067)	(0.058)	(0.059)	(0.059)	(0.062)
80%-100% general education: 3 Years	-0.198***	-0.242***	-0.138**	-0.153***	-0.121**	-0.072
	(0.057)	(0.051)	(0.042)	(0.041)	(0.045)	(0.053)
District FE		X	X	X	X	X
Student Demographics			X	X	X	X
Disability Type				X	X	X
Prior Test Scores					X	X
Peer Effects						X
Number students	4486	4486	4486	4486	4486	4486
Panel B: Predicting on-time graduation						
Four or more CTE credits	0.027*	0.048***	0.040**	0.032*	0.033*	0.033*
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
80%-100% general education: 1 Year	0.039+	0.054*	0.052*	0.035+	0.023	0.012
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
80%-100% general education: 2 Years	0.115***	0.128***	0.127***	0.100***	0.077***	0.054**
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.019)
80%-100% general education: 3 Years	0.161***	0.179***	0.170***	0.140***	0.111***	0.075***
	(0.015)	(0.016)	(0.016)	(0.015)	(0.017)	(0.019)
District FE		X	X	X	X	X
Student Demographics			X	X	X	X
Disability Type				X	X	X
Prior Test Scores					X	X
Peer Effects						X
Number students	4445	4445	4445	4445	4445	4445
Panel C: Predicting enrollment in college in six months after expected graduation year						
Four or more CTE credits	-0.022	0.003	-0.006	-0.004	-0.004	-0.003
	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
80%-100% general education: 1 Year	0.061***	0.056***	0.054***	0.053**	0.034*	0.028
	(0.015)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
80%-100% general education: 2 Years	0.106***	0.087***	0.082***	0.081***	0.045*	0.033+
	(0.018)	(0.018)	(0.017)	(0.018)	(0.019)	(0.018)
80%-100% general education: 3 Years	0.184***	0.184***	0.168***	0.166***	0.110***	0.085***
	(0.015)	(0.016)	(0.016)	(0.016)	(0.018)	(0.018)
District FE		X	X	X	X	X
Student Demographics			X	X	X	X
Disability Type				X	X	X
Prior Test Scores					X	X
Peer Effects						X
Number students	4445	4445	4445	4445	4445	4445
Panel D: Predicting employment in six months after expected graduation year						
Four or more CTE credits	0.013	0.029**	0.027*	0.023*	0.022+	0.024*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
80%-100% general education: 1 Year	0.004	0.015	0.014	0.012	0.004	0.005
	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
80%-100% general education: 2 Years	0.061***	0.070***	0.069***	0.063***	0.052***	0.050**
	(0.013)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
80%-100% general education: 3 Years	0.065***	0.075***	0.074***	0.068***	0.053***	0.051**
	(0.012)	(0.013)	(0.013)	(0.014)	(0.015)	(0.016)
District FE		X	X	X	X	X
Student Demographics			X	X	X	X
Disability Type				X	X	X
Prior Test Scores					X	X
Peer Effects						X
Number students	4445	4445	4445	4445	4445	4445

NOTE : p-values from two-sided t-test : +p<0.1, *p<0.05, **p<0.01, ***p<0.001. Student demographics include lagged absences, race/ethnicity, gender, bilingual status, housing status, migrant status, English Language Learning status, highly capable/gifted status, and home school status. Standard errors are clustered at the school level.

Table 9. CTE and Inclusion Concentration Models, SLD Students Only

Panel A: Predicting number of absences in 12th grade						
Four or more CTE credits	-0.166*		-0.165*			
	(0.070)		(0.070)			
80%-100% general education: 1 Year		0.007	0.010			
		(0.106)	(0.106)			
80%-100% general education: 2 Years		0.021	0.023			
		(0.089)	(0.089)			
80%-100% general education: 3 Years		-0.083	-0.079			
		(0.076)	(0.076)			
Number students	2594	2594	2594			
Panel B: Predicting on-time graduation						
Four or more CTE credits	0.037*	0.025+			0.037*	0.025+
	(0.016)	(0.015)			(0.015)	(0.015)
80%-100% general education: 1 Year			-0.022	-0.022	-0.023	-0.023
			(0.025)	(0.023)	(0.025)	(0.023)
80%-100% general education: 2 Years			0.004	0.005	0.004	0.004
			(0.023)	(0.022)	(0.023)	(0.022)
80%-100% general education: 3 Years			0.034	0.029	0.033	0.028
			(0.021)	(0.021)	(0.021)	(0.021)
Student absences		-0.069***		-0.069***		-0.069***
		(0.008)		(0.008)		(0.008)
Number students	2568	2568	2568	2568	2568	2568
Panel C: Predicting enrollment in college in six months after expected graduation year						
Four or more CTE credits	-0.002	-0.007			-0.003	-0.008
	(0.018)	(0.018)			(0.018)	(0.019)
80%-100% general education: 1 Year			0.031	0.033	0.031	0.033
			(0.025)	(0.024)	(0.025)	(0.024)
80%-100% general education: 2 Years			-0.009	-0.010	-0.009	-0.009
			(0.026)	(0.026)	(0.026)	(0.026)
80%-100% general education: 3 Years			0.057*	0.054*	0.057*	0.054*
			(0.026)	(0.026)	(0.026)	(0.026)
Student absences		-0.014**		-0.013**		-0.013**
		(0.005)		(0.005)		(0.005)
On-time graduation		0.080***		0.078***		0.079***
		(0.020)		(0.020)		(0.020)
Number students	2568	2568	2568	2568	2568	2568
Panel D: Predicting employment in six months after expected graduation year						
Four or more CTE credits	0.029+	0.027+			0.028+	0.026+
	(0.015)	(0.015)			(0.015)	(0.015)
80%-100% general education: 1 Year			0.008	0.009	0.007	0.009
			(0.022)	(0.021)	(0.022)	(0.022)
80%-100% general education: 2 Years			0.042+	0.042+	0.042+	0.041+
			(0.023)	(0.022)	(0.023)	(0.022)
80%-100% general education: 3 Years			0.037	0.035	0.036	0.035
			(0.023)	(0.023)	(0.023)	(0.023)
Student absences		0.001		0.000		0.001
		(0.005)		(0.005)		(0.005)
On-time graduation		0.058**		0.058**		0.057**
		(0.020)		(0.020)		(0.020)
Number students	2568	2568	2568	2568	2568	2568

NOTE : p-values from two-sided t-test : +p<0.1, *p<0.05, **p<0.01, ***p<0.001. All models control for lagged absences, race/ethnicity, gender, bilingual status, housing status, migrant status, English Language Learning status, highly capable/gifted status, home school status, a cubic polynomial of 8th grade WASL scores, disability type, number of years diagnosed with a disability since 7th grade, peer effects, and include a district fixed effect. Standard errors are clustered at the school level.

Table 10. CTE Concentration and Inclusion Models, non-SLD Students Only

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Predicting number of absences in 12th grade						
Four or more CTE credits	-0.223**		-0.220**			
	(0.075)		(0.075)			
80%-100% general education: 1 Year		-0.038	-0.023			
		(0.110)	(0.110)			
80%-100% general education: 2 Years		-0.100	-0.079			
		(0.094)	(0.094)			
80%-100% general education: 3 Years		-0.025	-0.010			
		(0.090)	(0.090)			
Number students	1892	1892	1892			
Panel B: Predicting on-time graduation						
Four or more CTE credits	0.033	0.023			0.027	0.017
	(0.024)	(0.023)			(0.024)	(0.024)
80%-100% general education: 1 Year			0.052	0.050	0.050	0.049
			(0.036)	(0.036)	(0.036)	(0.036)
80%-100% general education: 2 Years			0.116**	0.112**	0.113**	0.110**
			(0.035)	(0.034)	(0.035)	(0.034)
80%-100% general education: 3 Years			0.150***	0.149***	0.148***	0.148***
			(0.035)	(0.034)	(0.035)	(0.034)
Student absences		-0.043***		-0.043***		-0.042***
		(0.013)		(0.013)		(0.012)
Number students	1877	1876	1877	1876	1877	1876
Panel C: Predicting enrollment in college in six months after expected graduation year						
Four or more CTE credits	-0.006	-0.013			-0.010	-0.016
	(0.023)	(0.023)			(0.023)	(0.023)
80%-100% general education: 1 Year			0.011	0.006	0.012	0.007
			(0.027)	(0.026)	(0.027)	(0.027)
80%-100% general education: 2 Years			0.081*	0.069*	0.082*	0.070*
			(0.034)	(0.034)	(0.034)	(0.034)
80%-100% general education: 3 Years			0.110***	0.096**	0.111***	0.097**
			(0.030)	(0.030)	(0.030)	(0.030)
Student absences		-0.016*		-0.015*		-0.016*
		(0.008)		(0.007)		(0.007)
On-time graduation		0.103***		0.092***		0.092***
		(0.019)		(0.020)		(0.020)
Number students	1877	1876	1877	1876	1877	1876
Panel D: Predicting employment in six months after expected graduation year						
Four or more CTE credits	0.028+	0.025			0.026	0.023
	(0.016)	(0.017)			(0.016)	(0.016)
80%-100% general education: 1 Year			0.002	-0.001	-0.000	-0.003
			(0.017)	(0.017)	(0.017)	(0.017)
80%-100% general education: 2 Years			0.059*	0.052*	0.056*	0.050*
			(0.023)	(0.023)	(0.023)	(0.023)
80%-100% general education: 3 Years			0.068**	0.060*	0.066**	0.058*
			(0.024)	(0.024)	(0.023)	(0.023)
Student absences		-0.009*		-0.009*		-0.009*
		(0.004)		(0.004)		(0.004)
On-time graduation		0.061***		0.055***		0.054***
		(0.014)		(0.014)		(0.014)
Number students	1877	1876	1877	1876	1877	1876

NOTE : p-values from two-sided t-test : +p<0.1, *p<0.05, **p<0.01, ***p<0.001. All models control for lagged absences, race/ethnicity, gender, bilingual status, housing status, migrant status, English Language Learning status, highly capable/gifted status, home school status, a cubic polynomial of 8th grade WASL scores, disability type, number of years diagnosed with a disability since 7th grade, peer effects, and include a district fixed effect. Standard errors are clustered at the school level.

Figure 1. 8th Grade WASL Reading Score by Level of Inclusion in 12th Grade