The Adulthood Outcomes of Students in Special Education Services across Two Time Points using Propensity Score Analyses

Tomoe Kanaya Jacey Carter

Claremont McKenna College

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Abstract

The current working paper examines the adulthood outcomes of students who received special education services with students who did not receive services across two time points using propensity score analyses on the NLSY79 Child and Young Adult (CYA) dataset. Educational and financial variables collected in 2012 from a previously published study were updated using the 2018 CYA datawave. New outcome variables that broadened the measure of "economic self-sufficiency" were also included. Findings revealed that, similar to the results on the 2012 outcomes, propensity for receiving services continued to be a significant predictor on multiple 2018 outcomes. Most of the significant findings between race/ethnicity and special education, however, were not replicated on the 2018 outcomes. The findings are discussed within the context of economic and educational policies that affect children with disabilities and issues surrounding longitudinal research methodology.

Keywords: IDEA, economic outcomes, propensity score, longitudinal methodology

Introduction

Costing over fifty billion dollars and serving over six million school children each year, the Individuals with Disabilities Education Act (IDEA, 34 C.F.R. § 300.8, 2004) is an integral part of the American educational system. The purpose of IDEA is to ensure that children with disabilities experience "quality of opportunity, full participation, independent living and economic self-sufficiency" through services that are tailored to their disabilities. The inclusion of "independent living and economic self-sufficiency" demonstrates the importance of preparing children with the ability to live productive and independent lives beyond the school years. Despite this, an overwhelming majority of the research on special education focuses on school-aged outcomes (Fisher, Spooner, Algozzine, Anderson, Brosh, & Robertson, 2019), and far less is known about the relationship between receiving special education services on post-secondary outcomes (Cushing, Parker-Katz, Athamanah, Walte, & Pose, 2020). Therefore, more research on how children in special education fare into adulthood is needed to understand the long-term impact of this policy.

Research findings on special education can be difficult to interpret due to issues surrounding selection bias. Specifically, children who receive services differ significantly from children who do not on many characteristics including race, sex, birth weight, maternal cognitive ability and educational attainment, socio-economic status, prenatal health, neighborhood quality, and preschool attendance (e.g., Donovan & Cross, 2002). Therefore, it is difficult to determine the appropriate comparison group needed to make valid conclusions regarding the special education population.

Many researchers advocate the use of propensity score (PS) analyses to alleviate these concerns of selection bias within special education research (Morgan, Frisco, Farkas & Hibel, 2017; Sullivan & Field, 2013). This approach allows researchers to create a dataset where half of the individuals received special education services, even though everyone was *equally* likely to do so based on the contextual factors listed above. While this procedure cannot be seen as a substitute for random assignment, it has been shown to lead to more unbiased results (Rosenbaum & Rubin, 1983).

Longitudinal research in special education: The advantages of the NLSY datasets

PS studies on the Early Childhood Longitudinal Study datasets reveal very few improvements among children in special education, compared to their counterparts (Morgan et al., 2017; Sullivan & Field, 2013). However, it is important to remember that individuals in these datasets are still in school and may not have experienced the full benefits of IDEA services. Unfortunately, due to the age of the participants, examining adulthood outcomes with these databases will not be possible for many years.

The National Longitudinal Transition (NLT) datasets were created to examine the adulthood outcomes of students who received special education services in high school. Using the NLT-2, Newman, Madaus and Javitz (2016) utilized PS methods on these data and found that students who received transitional planning services as part of their special education services were more likely to receive disability-related support at career and technical education schools compared to students who did not have a transition plan. The NLT datasets, however, follow individuals who were receiving special education services during the ages of 13 to 16, and individuals who did not receive services cannot be included as a comparison group.

Conducting PS analysis on the National Longitudinal Survey of Youth 1979 (NLSY) and its corresponding Child and Young Adult dataset (CYA), however, provides the opportunity to examine adulthood outcomes while using an appropriate comparison group of students who did not receive services, but were equally likely to do so. The NLSY is comprised of individuals who were between 14 and 21 years old on December 31, 1978, and were interviewed biennially on a wide range of behaviors, including income, cognitive ability, physical health, and occupational status. The CYA, created in 1986, tracks the children born to the females of the NLSY.

Similar to the NLSY, the CYA were interviewed biennially about their emotional, social and physical behaviors, as well as their educational and occupational patterns. By combining the information from both datasets, it is possible to create a comprehensive, longitudinal dataset that includes children's individual and environmental characteristics (e.g., birth weight, developmental milestones, home quality), as well as maternal characteristics (e.g., maternal education, maternal aptitude) for calculating PS for special education, allowing for an appropriate comparison group. Due to the age ranges within the CYA, it is also possible to examine adulthood outcomes across the lifespan. Therefore the NLSY and CYA are an optimal datasource for conducting PS analyses on adults who previously received special education services.

Previous findings on CYA participants

Kanaya, Wai and Miranda (2019) conducted PS analyses on the NLSY and CYA datasets to compare individuals who received special education services with those who did not on multiple adulthood outcomes, including economic self-sufficiency (e.g., highest yearly income, welfare use, use of public assistance). The results suggest that Hispanic students in their sample who participate in special education fared better compared to their non-Hispanic counterparts on some outcomes. Moreover, propensity (the likelihood of receiving services) predicted several outcomes. These results suggest that the benefits of receiving special education services is dependent on race and ethnicity. They further suggest that the context that surrounds the likelihood of receiving special education services plays a stronger role in these outcomes than receiving the services.

These analyses, however, were conducted on the outcomes collected from the 2012 datawave of the CYA, and therefore, only represent one point of time within adulthood. Adults continue to grow and develop as they continue to experience important milestones and challenges, including childcare, further education and career training, and elder care issues. Therefore, further follow-ups are required in order to determine the full trajectory of these outcomes across the lifespan.

In addition to using updated outcome data, additional variables that measure the domains functional living and economic self-sufficiency are warranted. For example, some individuals may not have the pressure of securing a job at a specific time point in adulthood because they have the security of family members and friends who are willing and able to cover their living expenses and provide them with housing in safe neighborhoods. Further, health and access to health insurance are important factors within economic stability (Dean 2002). Despite the immediate connections between these variables and economic self-sufficiency, they were not included in the original analyses. Therefore, the purpose of the current working paper was to update the original findings by Kanaya et al. (2019) by replicating the analyses using the most recently available, 2018 CYA datawave and by including new outcome variables that provide a broader assessment of functional living and economic self-sufficiency.

Method

Participants

Following the procedures outlined by Rosenbaum and Rubin (1983) and Little and Rubin (2014), PS for receiving special education services was calculated for each participant (*n* = 7,111) using 38 variables (see Table 1). Each CYA who received services was matched with a CYA who did not receive services with the same propensity score. Due to ethnic and gender disparities found within special education participation, the propensity score calculations and subsequent matchings were done separately for each race-by-gender subgroup (i.e., ensuring that a Black male will be matched with a Black male). A series of t-tests were conducted to ensure the subgroups were balanced across all covariates and propensity scores. The resulting sample consisted of 586 participants (see Table 2 for final sample demographics).

Outcome Measure

A series of outcome measures were selected and categorized using four of the domains outlined by Ysseldyke and Olsen (1997): educational attainment, economic self-sufficiency, social adjustment, and physical health. These domains are part of a proposed framework for assessing the performance and progress of children with disabilities, developed in part to address the IDEA policy requiring states to use alternate assessments for students who cannot take standard forms of assessment.

Five outcomes (highest grade completed, high school diploma, physical health, social support and family conflict) served as an updated replication of previous analyses on 2012 outcomes (Kanaya et al, 2019) and used to compare outcomes over time. Four outcomes (yearly income, public assistance, substance abuse, and conviction) were modified from the initial analysis on the 2012 outcomes. These modifications were made to assess the relationship between special education and behavioral patterns at a specific point in time (2018) rather than as a cumulative experience across the lifespan. Finally, four outcomes (someone pay rent, any college attendance, number of illnesses, and neighborhood quality) were analyzed to provide a broader examination of the role of special education on these domains. Each outcome measure within each domain is described below.

Economic Self-Sufficiency

Yearly Income (modified). Participants were asked to report their yearly income. The log-transformation was used for the current paper (see explanation in Results section).

Use of Any Form of Public Assistance (modified). During all waves of data collection, participants were asked to report whether they received federal assistance from the following programs: welfare, food stamps, Woman, Infants and Children (WIC), or Aid to Families with Dependent Children (AFDC). Using this data, a dichotomous variable was created indicating whether participants reported **ever** receiving any form of public assistance by 2012 was used in Kanaya et al. (2019). For the current paper, participants' dichotomous response for use of public assistance during 2018 was used.

Did Someone Pay Rent (New Variable). Participants were asked to report if anyone (other than spouse or partner) paid for part of their living expenses that year.

Educational Attainment

Highest Grade Completed. During all waves of data collection, participants were asked to report the highest grade they completed. A variable was created indicating the highest grade reported across waves.

High School Diploma. Using participant reports of grade completion, a variable was created indicating whether participants received a high school diploma. If participants reported receiving a high school diploma, a separate variable was created to indicate the year participants received this degree.

Any College Attendance (New Variable). Using participant reports of college attendance, specifically from 2012 to 2018, data was collected indicating whether participants had any college attendance. A dichotomous variable was created indicating whether participants reported college attendance across any of the years observed.

Physical Health

Physical Health Self-Rating. Participants rated their physical health on a 5-point Likert scale (1 = poor, 2 = fair, 3 = good, 4 = very good, 5 = excellent).

Ever Used Marijuana, Stimulants and/or Cocaine (modified). During all waves of data collection, participants were asked to report their drug use, including their use of marijuana, stimulants and/or cocaine. Using this data, a dichotomous variable was created indicating whether participants reported ever using these drugs by 2012 was used in Kanaya et al. (2019). For the current paper, participants' dichotomous response for drug use during 2018 was used.

Health Insurance (New Variable). Participants were asked if they are currently covered by any kind of health insurance or health care plan.

Illnesses this Year (New Variable). Participants were asked to provide the number of illnesses that required medical attention or treatment in the past 12 months.

Social Adjustment

Social Support. Four items were used to assess the extent to which participants felt supported by family and friends. Items included, "*How much do you feel loved and cared for by your* *relatives?*" and "*How much can you open up to your friends if you need to talk about your worries?*" Participants rated the items on a 5-point Likert scale (1 = not at all, 2 = a little, 3 = some, 4 = quite a bit, 5 = a great deal). The social support score was based on a mean of the four items (Cronbach α = 0.77).

Family Conflict. A six-item scale was used to assess the degree of conflict in participants' families. Items included, "*We fight a lot in our family*," "*Family members hardly ever lose their temper*," "*Family members sometimes get so angry they throw things*," and "*Family members always calmly discuss problems*." The six-item Family Conflict Scale is a subset of the Family Environment Scale (Moos and Moos, 1994). Participants rated the items on a 4-point Likert scale (1 = strongly agree, 2 = agree, 3 = disagree, 4 = strongly disagree). These ratings were reverse coded to indicate that a higher score (e.g., 4) meant a higher level of family conflict compared to a lower score (e.g., 1). The family conflict scale is based on a mean of all six items (Cronbach α = 0.74).

Conviction (Modified). During all waves of data collection, participants were asked to report whether they were ever convicted of a felony. A dichotomous variable was created indicating whether participants reported **ever** using these drugs by 2012 was used in Kanaya et al. (2019). For the current paper, participants' dichotomous response for conviction during 2018 was used.

Neighborhood Quality (New Variable). Eight items were used to assess the extent to which participants considered their neighborhood was problematic. Items included, "*There are lots of people who cannot find jobs"* and *"There are abandoned or run-down buildings."* Participants rated the items on a 3-point Likert scale (1 = a big problem, 2 = somewhat of a problem 3 = not a problem). The neighborhood quality score was based on a mean of the eight items.

Results

A total of 13 multiple regression and multiple binary logistic regression analyses were conducted to compare the educational attainment, economic self-sufficiency, physical health, and social adjustment of individuals who received special education services (the treatment group) to those who did not (the control group). Each regression model assessed the main effects of special education and included birth year, gender, and race/ethnicity to control for the age range represented in the dataset and potential differences related to demographic variables. Propensity was included as a covariate in order to reduce bias (Rosenbaum and Rubin, 1985) and control for the likelihood of receiving services. Finally, all corresponding 2-way interactions between race/ethnicity and special education, as well as gender and special education were tested to determine whether the effects of special education varied by race/ethnicity or gender.

Exact Replications

Highest Grade Completed

The 2018 model for highest grade completed was significant, $F(9,340) = 5.87$, $p<0.01$; ${}_{adj}R^2= 0.11$. Propensity was significant, $B = -3.22$, $p = 0.0000803$, such that individuals with higher propensity for special education attained lower levels of education than individuals with higher propensity. Birth year was significant, $B = 0.098$, $p < 0.001$, indicating that younger participants attained higher levels of education compared to older participants. Race/ethnicity was also significant for Hispanics, $B= -1.19$, $p < 0.05$, indicating that Hispanics attained higher levels of education compared to non-Hispanics (see Table 1).

This is similar to the 2012 model, where the was significant, $F(9, 422) = 3.18$, $p = 0.001$, $adjR2 = 0.04$. Propensity, $B = −1.61$, $p = 0.01$, and race/ethnicity was also significant (Hispanic:

$B = -0.90$, $p < 0.001$, Black: $B = -0.48$, $p < 0.05$) indicating that **both** Black and Hispanic children attained lower levels of education compared to Whites at this time.

High School Diploma (Binary)

The 2018 model for a high school diploma was significant, $\chi 2(9) = 28.79$, $p < 0.01$, *LLH* = -197.98, *Nagelkerke* $R^2 = 0.07$. Birth year was significant, $B = 0.396$, $p < 0.05$, such that older individuals had a higher likelihood of attaining a high school diploma compared to younger individuals. The Hispanic by Special Education interaction was significant, $B = -1.65$, $p < 0.05$, indicating that Hispanics who received special education had a lower likelihood of attaining a high school diploma compared to non-Hispanics who did not receive special education services. All other terms were nonsignificant (see Table 2).

These results are different from the 2012 models, which was significant, $\chi 2(9) = 34.50$, $p < 0.001$, $-2LL = 673.11$, *Nagelkerke* $R^2 = 0.08$. Propensity was significant, $B = -1.23$, $p < 0.05$, gender (female) was significant, $B = 0.56$, $p < 0.01$, and race/ethnicity was significant (Hispanic: $B = -0.77$, $p < 0.01$).

Physical Health

The 2018 model for physical health was not significant, $F(9, 339) = 2.382$, $p < 0.05$, ${}_{adj}R^2$=0.03. Sex was significant, $B = -0.407$, $p < 0.01$, such that females had lower health ratings compared to males. Race/ethnicity was significant, $B = 0.3934$, p<0.05, such that Blacks had higher health ratings compared to non-Blacks. The Sex x Special Education interaction was significant, $B = 0.482$, p<0.05, such that females who received special education services had higher health ratings compared to males who did not receive special education services. All other terms were nonsignificant (see Table 3).

These results are different from the 2012 model, which was significant, $F(9, 545) = 2.10$, $p < 0.05$, ${}_{adj}R^2 = 0.02$. The Hispanic x Special Education interaction was significant, $B = 0.66$, $p < 0.01$. All other terms were nonsignificant.

Social Support

The 2018 model for social support was not significant, $F(9, 336) = 1.169$, $p > 0.01$, ${}_{adj}R^2 = 0.004$. All terms were nonsignificant (see Table 4). The 2012 model **was** significant, $F(9, 542) = 4.75$, $p < 0.001$, ${}_{adj}R^2 = 0.06$. Gender was significant, $B = 0.23$, $p < 0.01$, and race/ethnicity was significant (Hispanic: $B = -0.36$, $p < 0.001$, Black: $B = -0.29$, $p < 0.01$).

Family Conflict

The 2018 model for family conflict was significant, $F(9, 339) = 3.2$, $p < 0.001$, ${}_{adj}R^2 = 0.05$. Race/ethnicity was significant, Black $B = -0.226$, $p < 0.01$, such that Blacks reported higher levels of family conflict compared to non-Blacks. All other terms were nonsignificant (see Table 5).

These results were different from the 2012 model, which was significant, $F(9, 545) = 5.41$, $p < 0.001$, ${}_{adj}R^2 = 0.07$. Special education was significant, $B = 0.09$, $p < 0.05$. Race/ethnicity was also significant for Hispanics **and** Blacks (Hispanic: $B = -0.20$, $p < 0.001$, Black: $B = -0.26$, $p < 0.001$). Finally, the Hispanic x Special Education interaction was significant, $B = 0.24$, $p < 0.05$. All other terms were nonsignificant.

Modified Replications:

Log-Transformed 2018 Income vs 2012 Income

The multiple regressions for income and log-transformed income reported in 2018 were conducted. After a careful examination of the normal probability plots of the residuals, the log-transformed model was chosen for reporting and interpretation. The model was significant, $F(9, 151) = 3.525$, $p < 0.001$, ${}_{adj}R^2 = 0.12$. Birth year was significant, $B = -.0015$, $p < 0.05$, such that older individuals had lower income than younger individuals. The Hispanic x Special Education interaction was significant, $B = 0.055$, $p < 0.05$, such that Hispanics who received special education services had higher income compared to non-Hispanics who did not receive services. All other terms were nonsignificant (see Table 6).

This was a slight change from the 2012 model, which was conducted on income without a log-transformation after a careful inspection of the normal probability plot of the residuals. The model was significant, $F(9, 508) = 12.44$, $p < 0.001$, $adjR2 = 0.17$). Birth year was significant, $B = -1900.13$, $p < 0.001$, gender (female) was significant, $B = -4707.47$, $p < 0.01$, and race/ethnicity for Blacks was significant, $B = -5289.36$, $p < 0.01$. All other terms were nonsignificant.

Used Any Form of Public Assistance in 2018 (Binary) vs Ever Used Public Assistance in 2012

The 2018 model for any form of public assistance was significant, $\chi2(9) = 23.823$, $p < 0.01$, LL = -61.480, *Nagelkerke* $R^2 = 0.162$. Propensity was significant, $B = 3.84$, $p < 0.05$, such that individuals with higher propensity for special education were more likely to receive any form of public assistance compared to individuals with lower propensity. All other terms were nonsignificant (see Table 7).

This was different from the 2012 model, which was also significant, $\chi2(9) = 120.82$, $p < 0.001$, $-2LL = 675.76$, *Nagelkerke* $R^2 = 0.25$. Propensity was significant, $B = 1.42$, $p < 0.05$, birth year was significant, $B = -0.21$, $p < 0.001$, and gender (female) was significant, $B = 0.62$, $p < 0.01$. All other terms were nonsignificant.

Used any Drugs in 2018 vs Ever Used any Drugs in 2012 (Binary)

The 2018 model for drugs was not significant, $\chi^2(9) = 18.36$, $p < 0.05$, LL = -283.78, *Nagelkerke* $R^2 = 0.03$. Birth year was significant, $B = 0.1$, $p < 0.001$, such that younger individuals were more likely to have taken drugs compared to older individuals. All other terms were nonsignificant (see Table 8).

These results were different from the significant 2012 model, $\chi^2(9) = 37.15$, $p < 0.001$, $-2LL = 769.06$, *Nagelkerke* $R^2 = 0.08$). Birth year was significant, $B = -0.10$, $p < 0.001$, and gender (female) was significant, $B = -0.63$, $p < 0.01$. All other terms were nonsignificant.

Convicted of any Crimes in 2018 vs Ever been Convicted in 2012 (Binary)

The 2018 model for convicted was not significant, $\chi^2(9) = 13.267$, $p > 0.01$, LL = -66.758, *Nagelkerke* $R^2 = 0.09$. All terms were nonsignificant (see Table 9).

These results were very different from the 2012 significant model, $\chi^2(9) = 45.36$, $p < 0.001$, $-2LL = 564.70$, *Nagelkerke* $R^2 = 0.12$. Birth year was significant, $B = -0.14$, $p < 0.001$ and gender (female) was significant, $B = -1.13$, $p < 0.001$. All other terms were nonsignificant.

New Variables:

Illnesses This Year

The 2018 model for illnesses this year was not significant, $F(9, 336) = 1.898$, $p > 0.05$, $_{adj}R^2 = 0.023$. Sex was significant, $B = -1.14$, $p < 0.01$, such that females reported less illnesses this year compared to males. The Sex x Special Education interaction was significant, $B = -1.04$, $p < 0.05$, such that females who received special education services had fewer illnesses this year than males who did not receive services. All other terms were nonsignificant (see Table 10).

Have Health Insurance

The 2018 model for health insurance was not significant, $\chi^2(9) = 10.003$, $p > 0.05$, $LL = -61.480$, *Nagelkerke* $R^2 = 0.162$. All terms were nonsignificant (see Table 11).

Someone Else Pay Rent

The 2018 model for someone paying rent was significant, $\chi^2(9) = 17.492$, $p > 0.05$, $LL = -139.737$, *Nagelkerke* $R^2 = 0.059$. Birth year was significant, $B = 0.126$, $p < .01$, such that younger individuals had an increased likelihood of someone paying rent compared to older individuals. All other terms were nonsignificant (see Table 12).

Neighborhood Quality

The 2018 model for neighbor quality was significant, $F(9, 336) = 1.917$, $p > 0.05$, $_{adj}R^2 = 0.023$. All terms were nonsignificant (see Table 13).

Any College Attendance

The 2018 model for any college attendance was significant, $\chi^2(9) = 17.441$, $p < 0.05$, $LL = -103.236$, *Nagelkerke* $R^2 = 0.078$. Propensity was significant, $B = 2.985$, $p < 0.01$, such that individuals with higher propensity for special education were more likely to receive any form of public assistance compared to individuals with lower propensity. All other terms were nonsignificant (see Table 14).

Conclusions

The results add to the limited research on the post-secondary experiences of children who received special education services. Specifically, special education did not play a significant role in the outcomes after controlling for all covariates. Propensity for special education, however, was a significant predictor of multiple outcomes in 2012 and 2018. In other words, the contextual variables (e.g., birth weight, test scores, maternal education) that determine the probability of receiving services were a significant predictor of outcomes, whereas receiving services was not. Finally, while race/ethnicity and gender were significant predictors in multiple outcomes in 2012, most of these findings did not hold in 2018, reflecting the complicated and dynamic role of race/ethnicity across the lifespan and in different contexts.

These results are similar to previous research that utilize propensity score analyses on school-aged outcomes (Morgan et al., 2017; Sullivan & Field, 2013). They also strongly suggest that challenging contextual factors, especially poverty, cannot be overcome by special education services alone. Therefore, in order to promote positive outcomes, programs that specifically target these contextual factors are particularly important when aiding children with disabilities. Future follow-up analyses should be conducted in order to determine if/how these longitudinal trajectories continue throughout the lifespan, including retirement planning and lifestyle. Given the sample size constraints, and issues surrounding missing data at different data wave collections, individual growth modeling would be a particularly appropriate approach that will allow future researchers to examine individual variations across multiple time points (Curran, Obeidat & Lodardo, 2010; Singer & Willet, 2003).

While most of the findings on the new variables were not significant, the significant findings on the number of illnesses was a notable exception. Females reported, on average, more illnesses than males while females in special education reported fewer illnesses than males not in special education. Taken together, special education seems to have a 'double protection' effect for females compared to males, after controlling for all covariates. These findings emphasize the importance of examining a mult-faceted outcome, like health, through multiple outcome measures. More research using latent class analysis or mediational modeling, however, is needed in order to understand and to interpret this result within the context of health and adulthood development.

The one-to-one matching technique based on propensity scores is used by researchers to imitate random assignment, which is legally impossible within IDEA policy. Only a few datasets have the necessary data needed to enable propensity score analyses on special education participation, and to date, the study Kanaya and colleagues (2019) is (to date) the only known work that utilizes the strict, one-to-one criteria compared to the less conservative, strata-matching criteria. It is important to note, however, that propensity scores are not considered a substitution for random assignment, but rather, the best alternative when random assignment is not possible (Rosenbaum & Rubin, 1983).

Finally, it is important to recognize that the main effects from the 2012 outcomes were reported based on a series of *hierarchical,* multiple regression and *hierarchical*, multiple binary logistic analyses and reflect the coefficients from the first step, which did not include the interaction terms (see Kanaya et al., 2019 for specific details). The main effects from the 2018 outcomes, however, were reported from the model that included the interaction terms. The specific fit statistics for the binary regressions were also altered slightly from the original 2012 outcomes (e.g., LLH was reported instead of -2LLH). These changes were made in order to provide the second author with the most exposure to new statistical techniques, including the addition of new outcome variables and gaining experience with R/RStudio. These differences, however, are subtle and do not alter the overall interpretation of the findings.

Economic Policy Implications and Future Directions

Costing over fifty billion dollars, IDEA is currently one of the main sources of educational support for students with disabilities. Students who receive special education services, however, represent a wide range of abilities and contextual characteristics. Indeed, the cost of special education services can range from $500 to over $9,000 per student, depending on the severity of the disability and the types of services provided (Education Commission of the States, 2019). While the strict one-to-one matching reduces potential bias compared to the strata-matching technique, it also limits the analyses to individuals who have the same propensity score in the treatment and control conditions. Therefore, the impact of special education on students with severe disabilities who are receiving the costliest services throughout their school years cannot be examined with these data. Rather, these results are appropriate for students who are on the cusp of qualifying for services, and most likely represent students who are receiving lower-cost services for shorter durations and have the least financial impact on IDEA. Despite this, these preliminary findings suggest that the (potentially minimal) costs of providing services to students at the cusp of qualifying for services are receiving few benefits in adulthood compared to their non-serviced counterparts.

For some outcomes, birth year negatively predicted two economic outcomes in 2018 (income and someone else paying rent/living expenses). This was unexpected given age is usually positively correlated with income and financial independence. This may be due to specific circumstances like the housing crisis of 2008 that made older adults more vulnerable to financial risks and debt than their younger counterparts and grown children (Mather, 2015). These results may also be due to changes in the quality of the programs that assist individuals with disabilities and those who are likely to receive special services over time. For example, state expenditures on specific programs or districts may vary between years, resulting in different levels of funding and resources for education each year (Murray 1998). In other words, younger cohorts may be attending school at a period in time where there are better resources, higher quality services, and reliable teaching. Future research that examines these trends through the lens of a year by geographic region interaction could provide valuable insights on when, how, and where specific reform is needed in order to prepare students with disabilities for the workforce

This pattern may also reflect the changes in the labor market demands across the lifespan, regardless of geographical location. For example, STEM jobs, which are associated with strong labor market payoffs, including higher wages at entry level (Carnevale, Cheah & Strohl, 2012; Deming & Noray, 2020), also experience salary declines by more than 50 percent within 10 years. This ‘reversal in fortune’ is due to the rapidly changing demands in skills in STEM occupations, underscoring the need for continuing education and training to remain in the STEM workforce (Deming & Noray, 2020). The participants in the current sample are most likely to be vulnerable to such changes, as women, minorities and individuals with disabilities continue to be under-represented in the highest earning professions, including STEM (Cech & Blair-Loy; National Center for Science and Engineering Statistics, 2021). Further, it can be argued that individuals in *most* occupations are affected by these changes as technological advances continue to automate jobs across many industries and at all levels, from the use of automated cash registers in grocery stores to artificial intelligence algorithms in corporate finance. Therefore, programs and policies that provide continuing educational and career support in middle adulthood may be warranted in order to increase their retention and continued growth in the workforce.

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Table 1

Results of the Multiple Regression Analyses Predicting Highest Grade Completed

Predictor Variables	*B*	*SE(B)*	$\boldsymbol{\beta}$	*p*
Constant	-191.292	60.764	0.000	0.002
Propensity	-3.220	0.807	0.212	0.000
Special ed (1, yes)	0.269	0.419	0.054	0.521
Birth Year	0.098	0.031	0.166	0.001
Sex (1, female)	0.433	0.375	-0.083	0.249
Hispanic (1, yes)	-1.195	0.468	-0.197	0.011
Black (1, yes)	-0.779	0.414	-0.143	0.061
Hispanic x Special Ed	0.109	0.654	0.014	0.868
Black x Special Ed	-0.313	0.587	-0.044	0.594
Sex x Special Ed	-0.554	0.525	-0.085	0.292

$F(9,340) = 5.872$, $p<0.001$; ${}_{adj}R^2 = 0.112$

Table 2

Results of the Logistic Regression Analyses Predicting High School Diploma

Predictor Variables	*B*	*SE(B)*	*p*
Constant	-269.284	70.548	0.000
Propensity	-0.779	0.954	0.414
Special ed (1, yes)	0.830	0.425	0.051
Birth Year	0.134	0.035	0.000
Sex (1, female)	0.396	0.390	0.311
Hispanic (1, yes)	0.132	0.499	0.791
Black (1, yes)	0.423	0.430	0.325
Hispanic x Special Ed	-1.651	0.806	0.041
Black x Special Ed	-1.151	0.611	0.060
Sex x Special Ed	-0.365	0.543	0.501

$x^2(9) = 28.79$, $p<0.01$, $LL = -197.977$, *Nagelkerke* $R^2 = 0.068$

Table 3:
Results of the Multiple Regression Analyses Predicting Physical Health

Predictor variables	*B*	*SE(B)*	β	*p*
Constant	-13.569	24.332	0.000	0.577
Propensity	-0.426	0.328	0.072	0.195
Special ed (1, yes)	-0.192	0.167	-0.100	0.252
Birth Year	0.009	0.012	0.037	0.493
Sex (1, female)	-0.407	0.150	0.205	0.007
Hispanic (1, yes)	0.048	0.187	0.021	0.797
Black (1, yes)	0.393	0.166	0.188	0.018
Hispanic x Special Ed	-0.269	0.261	-0.088	0.305
Black x Special Ed	-0.115	0.235	-0.042	0.624
Sex x Special Ed	0.482	0.210	0.192	0.022

$F(9,339) = 2.382$, $p>0.01$; ${}_{adj}R^2 = 0.035$

Table 4:
Results of the Multiple Regression Analyses Predicting Social Support

Predictor variables	*B*	*SE(B)*	***β***	*p*
Constant	-5.355	24.124	0.00	0.824
Propensity	0.045	0.321	-0.008	0.888
Special ed (1, yes)	-0.047	0.166	-0.025	0.778
Birth Year	0.005	0.012	0.022	0.694
Sex (1, female)	0.244	*0.149*	-0.126	0.103
Hispanic (1, yes)	-0.192	0.187	-0.084	0.306
Black (1, yes)	-0.077	0.164	-0.038	0.64
Hispanic x Special Ed	-0.001	0.262	0.000	0.997
Black x Special Ed	-0.169	0.234	-0.063	0.469
Sex x Special Ed	0.002	0.209	0.001	*0.992*

$F(9,336) = 1.169$, $p>0.01$; $_{adj}R^2 = 0.004$

Table 5:
Results of the Multiple Regression Analyses Predicting Family Conflict

Predictor variables	*B*	*SE(B)*	$\boldsymbol{\beta}$	*p*
Constant	-6.354	8.566	0.000	0.459
Propensity	-0.140	0.114	0.067	0.221
Special ed (1, yes)	-0.086	0.059	-0.126	0.145
Birth Year	0.005	0.004	0.057	0.285
Sex (1, female)	0.074	0.053	0.104	0.164
Hispanic (1, yes)	-0.080	0.066	-0.097	0.224
Black (1, yes)	-0.226	0.058	-0.304	0.000
Hispanic x Special Ed	-0.028	0.092	-0.026	0.763
Black x Special Ed	0.102	0.083	0.104	0.221
Sex x Special Ed	0.054	0.074	0.060	0.469

$F(9,339) = 3.2$, $p<0.001$; ${}_{adj}R^2 =$ 0.054

Table 6:
Results of the Multiple Regression Analyses Predicting Transformed Income

Predictor variables	*B*	*SE(B)*	***β***	*p*
Constant	3.804	*1.604*	*0.000*	0.189
Propensity	0.051	0.022	0.181	*0.023*
Special ed (1, yes)	-0.016	0.010	*-0.172*	0.097
Birth Year	-0.002	0.001	-0.149	0.049
Sex (1, female)	-0.018	*0.011*	*0.269*	*0.090*
Hispanic (1, yes)	-0.024	*0.017*	*-0.185*	0.152
Black (1, yes)	*-0.010*	0.013	*-0.063*	*0.468*
Hispanic x Special Ed	*0.055*	*0.023*	0.135	0.016
Black x Special Ed	0.002	*0.021*	*-0.083*	*0.929*
Sex x Special Ed	*-0.015*	0.014	0.068	*0.301*

$F(9,151) = 3.525$, $p<0.001$; ${}_{adj}R^2 = 0.124$

Table 7:
Results of the Logistic Regression Analyses Predicting Use Any Form of Public Assistance

Predictor variables	*B*	*SE(B)*	*p*
Constant	14.523	1499.927	0.992
Propensity	3.841	1.245	0.002
Special ed (1, yes)	17.567	1493.619	0.991
Birth Year	-0.016	0.069	0.814
Sex (1, female)	0.827	*1.331*	0.534
Hispanic (1, yes)	0.172	2554.755	1.000
Black (1, yes)	17.0144	1493.619	0.991
Hispanic x Special Ed	0.601	2554.755	1.000
Black x Special Ed	-17.400	1493.619	0.991
Sex x Special Ed	-0.564	1.433	*0.694*

$x^2(9) = 23.823$, $p<0.01$, $LL = -61.480$, *Nagelkerke* $R^2 = 0.162$

Table 8:
Results of the Logistic Regression Analyses Predicting Use of Any Drugs

Predictor variables	*B*	*SE(B)*	*p*
Constant	-201.500	55.440	0.000
Propensity	-1.094	0.791	0.167
Special ed (1, yes; 0, no)	-0.291	0.354	0.411
Birth Year	0.100	0.028	0.000
Sex (1, female; 0, male)	-0.027	*0.319*	0.934
Hispanic (1, yes; 0, no)	-7.894	0.373	0.983
Black (1, yes; 0, no)	-0.225	0.359	0.531
Hispanic x Special Ed	0.660	0.514	0.200
Black x Special Ed	0.334	0.507	0.510
Sex x Special Ed	0.097	0.442	*0.826*

$x^2(9) = 18.364$, $p<0.05$, $LL = -283.776$, *Nagelkerke* $R^2 = 0.031$

Table 9:

Results of the Logistic Regression Analyses Predicting Conviction of any Crimes

Predictor variables	*B*	*SE(B)*	*p*
Constant	-198.725	139.078	0.153
Propensity	-3.501	2.422	0.148
Special ed (1, yes; 0, no)	-0.688	0.946	0.467
Birth Year	0.097	0.070	0.166
Sex (1, female; 0, male)	-16.412	1049.466	0.988
Hispanic (1, yes; 0, no)	0.292	0.947	0.758
Black (1, yes; 0, no)	0.234	0.947	0.805
Hispanic x Special Ed	0.901	1.319	0.494
Black x Special Ed	1.108	1.285	0.388
Sex x Special Ed	15.614	1049.466	0.988

$x^2(9) = 13.267$, $p>0.01$, $LL = -66.758$, *Nagelkerke* $R^2 = 0.090$

Table 10:

Results of the Multiple Regression Analyses Predicting Illnesses This Year

Predictor variables	*B*	*SE(B)*	***β***	***p***
Constant	72.580	54.883	0.000	0.322
Propensity	0.660	0.741	-0.050	0.374
Special ed (1, yes)	0.611	0.379	0.142	0.108
Birth Year	-0.036	0.028	-0.071	0.193
Sex (1, female)	1.142	0.340	0.256	0.00
Hispanic (1, yes)	-0.405	0.422	-0.078	0.339
Black (1, yes)	-0.183	0.377	-0.039	0.627
Hispanic x Special Ed	-0.1756	0.590	-0.026	0.766
Black x Special Ed	-0.395	0.534	-0.064	0.460
Sex x Special Ed	-1.044	0.475	-0.186	0.029

$F(9,336) = 1.898$, $p>0.05$; $_{adj}R^2 = 0.023$

Table 11:
Results of the Logistic Regression Analyses Predicting Health Insurance

Predictor variables	*B*	*SE(B)*	*p*
Constant	-57.594	*64.798*	0.374
Propensity	0.711	0.901	*0.430*
Special ed (1, yes; 0, no)	-0.174	0.452	0.700
Birth Year	0.030	0.033	0.350
Sex (1, male; 0, female)	-0.834	*0.436*	*0.056*
Hispanic (1, yes)	-0.854	*0.481*	0.076
Black (1, yes)	-0.398	0.457	*0.383*
Hispanic x Special Ed	1.043	*0.697*	0.135
Black x Special Ed	0.129	*0.628*	*0.838*
Sex x Special Ed	*-0.333*	0.597	*0.577*

$x^2(9) = 10.003$, $p>0.05$, $LL = -170.604$, *Nagelkerke* $R^2 = 0.028$

Table 12:
Results of the Logistic Regression Analyses Predicting Someone Else Paying Rent

Predictor variables	*B*	*SE(B)*	*p*
Constant	-254.576	84.080	0.002
Propensity	-1.012	1.0513	0.336
Special ed (1, yes)	0.303	0.475	0.523
Birth Year	0.126	0.042	0.003
Sex (1, male)	0.575	0.487	0.238
Hispanic (1, yes)	0.577	0.541	0.286
Black (1, yes)	0.136	0.528	0.797
Hispanic x Special Ed	-1.431	0.864	0.098
Black x Special Ed	0.073	0.706	0.918
Sex x Special Ed	-0.088	0.682	0.897

$x^2(9) = 17.492$, $p<0.05$, $LL = -139.737$, *Nagelkerke* $R^2 = 0.0589$

Table 13:

Results of the Multiple Regression Analyses Predicting Neighborhood Quality

Predictor variables	*B*	*SE(B)*	$\boldsymbol{\beta}$	*p*
Constant	-5.512	10.967	0.000	0.616
Propensity	-0.082	0.146	0.031	0.575
Special ed (1, yes)	0.097	0.076	0.112	0.202
Birth Year	0.004	0.006	0.040	0.460
Sex (1, female)	0.011	0.068	-0.013	0.866
Hispanic (1, yes)	-0.063	0.085	-0.060	0.460
Black (1, yes)	-0.087	0.075	-0.093	0.247
Hispanic x Special Ed	-0.125	0.119	-0.091	0.293
Black x Special Ed	-0.157	0.106	-0.127	0.142
Sex x Special Ed	0.056	0.095	0.050	0.554

$F(9,336) = 1.917$, $p<0.05$; $_{adj}R^2 = 0.023$

Table 14:
Results of the Logistic Regression Analyses Predicting Any College Attendance

Predictor variables	*B*	*SE(B)*	*p*
Constant	114.148	108.435	0.292
Propensity	2.985	1.093	0.006
Special ed (1, yes)	0.300	0.613	0.625
Birth Year	-0.058	0.054	0.289
Sex (1, male)	0.129	0.551	0.815
Hispanic (1, yes)	-0.911	0.580	0.117
Black (1, yes)	0.172	0.663	0.795
Hispanic x Special Ed	0.532	0.942	0.572
Black x Special Ed	-1.229	0.870	0.158
Sex x Special Ed	-0.029	0.765	0.970

$x^2(9) = 17.441$, $p<0.05$, $LL = -103.236$, *Nagelkerke* $R^2 = 0.078$