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Over Diagnosed or Over Looked? The Effect of Age at Time of School Entry On Students Receiving Special Education Services

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Much of the literature estimating disproportionality in special education identification rates has focused on socioeconomic status, race, and gender. However, recent evidence suggests that a student's school starting age also impacts the likelihood they receive special education services, particularly in the early grades. I build on the evidence that the youngest students in a grade more likely to be diagnosed with Attention Deficit/Hyperactivity Disorder and more likely to be placed in special education by estimating the effect of school starting age on special education identification in Michigan. I also estimate heterogeneity in this effect by student characteristics and across school districts. Using a regression discontinuity design exploiting variation in kindergarten starting age generated by a statewide kindergarten entrance age policy, I find that the youngest students in a kindergarten cohort are 40% more likely (3.3 percentage points, $p<0.001$) to be placed in special education than are the oldest students, and that this effect persists through eighth grade. Despite little evidence of heterogeneity by gender, race, or socioeconomic status, I find some suggestive evidence that the effect is particularly large for white boys in the early elementary grades and for black girls in the later elementary grades. I find no evidence that these effects vary across school districts. Finally, I find exploratory evidence of variation by school cohort age composition, suggesting these effects are driven moreso by relative age comparisons than absolute age developmental differences. Given the importance of special education services to the academic success of children with disabilities, these findings have implications for schools and for policymakers seeking to improve special education program provision.

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Abstract

Much of the literature estimating disproportionality in special education identification rates has focused on socioeconomic status, race, and gender. However, recent evidence suggests that a student's school starting age also impacts the likelihood they receive special education services, particularly in the early grades. I build on the evidence that the youngest students in a grade more likely to be diagnosed with Attention Deficit/Hyperactivity Disorder and more likely to be placed in special education by estimating the effect of school starting age on special education identification in Michigan. I also estimate heterogeneity in this effect by student characteristics and across school districts. Using a regression discontinuity design exploiting variation in kindergarten starting age generated by a statewide kindergarten entrance age policy, I find that the youngest students in a kindergarten cohort are 40% more likely (3.3 percentage points, $p<0.001$) to be placed in special education than are the oldest students, and that this effect persists through eighth grade. Despite little evidence of heterogeneity by gender, race, or socioeconomic status, I find some suggestive evidence that the effect is particularly large for white boys in the early elementary grades and for black girls in the later elementary grades. I find no evidence that these effects vary across school districts. Finally, I find exploratory evidence of variation by school cohort age composition, suggesting these effects are driven moreso by relative age comparisons than absolute age developmental differences. Given the importance of special education services to the academic success of children with disabilities, these findings have implications for schools and for policymakers seeking to improve special education program provision.

Over-diagnosed or overlooked? The effect of age at time of school entry on students receiving special education services

Special education is one of the most federally regulated areas of education policy in the United States and constitutes more than one fifth of federal spending on public elementary and secondary schools (U.S. Census Bureau, 2016). Despite the relatively strong federal role in special education policy, there is considerable local variation in special education participation underlying the 13% of students receiving services in public schools nationwide (NCES, 2017). For example, in 2015-2016 the percent of students participating in special education in New York was nearly 18%, compared with fewer than 9% of students in Texas. Even this state-level variation masks differences in special education rates by district and school. In Massachusetts, which has one of the highest rates of special education participation in the country (18%), district-level rates vary from 10-25% and school-level rates vary from 8% to 35% in the largest urban district (Massachusetts Department of Education, 2017).

Much attention has been paid to sociodemographic disparities and the school-, district- and state-level factors associated with differences in special education identification rates that may partially explain this considerable variation in special education participation across the country (Aron & Loprest, 2012; Cullen, 1999; Dhuey & Lipscomb, 2010; Hibel et al., 2010; Jacob, 2005; McManus et al., 2011; P. L. Morgan et al., 2015; Skiba et al., 2006; Sullivan & Val, 2013). A more recent line of inquiry has also found that the age at which children begin school can change the likelihood a child is placed in special education (Dhuey et al., 2019; Dhuey & Lipscomb, 2010) or diagnosed with Attention Deficit/Hyperactivity Disorder (ADHD) (Elder, 2010; Layton et al., 2018), with the youngest students in a grade cohort more likely to receive diagnoses than are the oldest students.

Although some studies have found a larger effect of school starting age for the youngest boys in the early years (Dhuey et al., 2019; Dhuey & Lipscomb, 2010), there is little evidence of heterogeneity in the effect of being young for grade by race or socioeconomic status. This is surprising given the large literature on disproportionality in special education identification by race and socioeconomic status that suggests that special education referral and evaluation practices are not applied consistently across demographic groups (Fish, 2017; O'Connor & Fernandez, 2002; Skiba et al., 2006). In contrast to student-level heterogeneity, little attention has been paid to whether there is heterogeneity in the effect of school starting age on special education receipt within a state. Differences in the demographic composition of individual school districts, teacher experience, and approaches to special education referral and evaluation could generate heterogeneity in the effects of school starting age across districts that has previously been unexplored in the literature.

Using state-level longitudinal data from Michigan for ten cohorts of entering kindergarten students, the current study adds to this growing body of literature by estimating the effect of school starting age on special education service receipt from kindergarten through middle school. More specifically, I use a regression discontinuity design that exploits exogeneous variation in school starting age generated by the state's kindergarten entrance policy to estimate the effect of being the youngest student in a kindergarten cohort on the likelihood of being placed in special education in kindergarten through 8th grade, whether this effect varies by gender, socioeconomic status, or race, and whether the effect varies by school district.

The present study makes several contributions to the literature. First, I add evidence that being young for grade impacts the likelihood of being placed in special education in Michigan, adding to earlier work identifying the same effect in Florida (Dhuey et al., 2019). Evidence from a new state context adds to our understanding of how the effect of school starting age generalizes to other settings with different polices and student populations. Second, I estimate heterogeneity in effects by gender-race subgroups to examine within-race heterogeneity by gender. The current study is also the first study to my knowledge that has estimated cross-district variation in the effect of school starting age on the likelihood of special education identification, and the first to my knowledge to apply the mixed multi-level hierarchical linear modeling approach to estimating cross-site variation in impacts developed by Bloom et al., (2017) within a regression discontinuity framework. Finally, I also provide evidence that the effect of school starting age on special education identification is driven by relative age comparisons rather than absolute age differences. These findings have implications for how we design policy solutions to address disparities in special education identification by school starting age, particularly in identifying at what level reforms may be most impactful.

Background

Much of the evidence that school starting age impacts disability diagnoses comes from the large body of literature on Attention Deficit/Hyperactivity Disorder (ADHD) diagnoses. The youngest children in a grade cohort are more likely to be diagnosed with ADHD in the United States (Elder, 2010; Evans et. al, 2010; Layton et. al, 2018), Germany (Schwandt & Wuppermann, 2016) the Netherlands (Krabbe et. al, 2014), and Canada (Ma et al., 2012). The detected effects range from a two to five percentage point increase or a 22-30% higher likelihood of ADHD diagnosis. The majority of these studies have used regression discontinuity designs, comparing students born just before and just after the kindergarten cutoff date to estimate the effect of being younger at entry on ADHD diagnosis. Further, many of these studies found that their estimated effects on likelihood of ADHD diagnosis were not detected for other conditions such as diabetes and hay fever in Germany (Schwandt & Wuppermann, 2016) and asthma, chicken pox, diabetes, and obesity in the United States (Evans et. al, 2010; Layton et. al, 2018) which supports the interpretation that the difference in ADHD diagnosis rates for younger students is not likely to be a reflection of absolute health differences between younger and older students.

Interestingly, a study in Denmark found no effect of age in grade on the likelihood of ADHD diagnosis after the age of 7, suggesting that differences in ADHD diagnoses are dependent on how doctors and teachers approach diagnosis in a given cultural context (Dalsgaard et. al., 2012). Further, clinicians in France use a different diagnostic manual to characterize, diagnose, and treat the behaviors associated with ADHD, resulting in fewer children diagnosed with and treated for ADHD overall and no evidence of age-related differences in ADHD diagnostic rates (Lecendreux, Konofal, & Faraone, 2011). These findings imply that overall prevalence of diagnosis may also influence whether age-in-grade impacts the likelihood of diagnosis.

However, the ADHD literature has focused on outcomes such as clinical diagnosis or stimulant prescriptions which may not directly correspond to special education identification. This is because the federal law requires not only that a child be found to meet the requirements for qualifying disability classifications but also that their disability creates a need for special education services (Individuals with Disabilities in Education Act, 2004). Further, most disability eligibility classification under IDEA do not require that a child have a clinical diagnosis, meaning that a child can be found eligible for services under education law but not have a medical diagnosis (National Research Council, 1997). For example, only three states require that a child have a clinical diagnosis of Autism or an Autism Spectrum Disorder in order to be classified with a primary disability of Autism under IDEA (MacFarlane & Kanaya, 2009).

Despite the consistent evidence that the youngest students in a grade in the United States are more likely to be given an ADHD diagnosis and the potential applicability to education outcomes, less attention has been paid to the effect of starting age on likelihood of being placed in special education services across disability types more generally, including for students with ADHD. In one study using data from the Early Childhood Longitudinal Study 98-99 (ECLS-K 98), the National Education Longitudinal Study (NELS) and the Education Longitudinal Study (ELS), the authors found that an additional month of age decreases the likelihood of receiving special education services by 2-5 percentage points (Dhuey & Lipscomb, 2010). However, this study relied on parent reports of disability rather than the administrative education records or health insurance records used in more recent studies. Parent reports of disability are not always consistent with receipt of special education (Marder, 2009), which may limit the applicability of these findings to special education participation.

A more recent study that combines Florida education and health records found a similar age effect, with the oldest students who were born in September 4-6 percentage points less likely to receive special education services than the youngest students, who were born in August (Dhuey et al., 2019). Using birth month and year, the authors estimated the effect of entering kindergarten at a younger age induced by a student's birth month in relation to the statewide kindergarten cutoff using fuzzy regression discontinuity design. The primary outcomes included kindergarten readiness scores, elementary and middle school test scores, disability classification, gifted education participation, likelihood of redshirting, grade retention, and likelihood of high school graduation. This study also used rich data on maternal and child health to demonstrate that the disability results were robust to including prenatal, birth, and family characteristics often hypothesized to be correlated with birth month. Overall, these findings provide strong evidence to support earlier findings that younger students are more likely to be given a disability classification and provide new evidence that these effects are robust to controlling for a number of family and health characteristics that had previously been understudied in this area of research.

Heterogeneity in the effect of being young for grade on special education identification

There is mixed evidence of heterogeneity by student characteristics underlying this average effect of school starting age on disability classifications. Overall, boys are more likely to be diagnosed with ADHD than girls, but authors have found conflicting evidence that the effect of school starting age on ADHD diagnoses is equal for boys and girls (Evans et al., 2010), larger for girls (Ma et al., 2012) or larger for boys (Layton et al., 2018). Similarly, boys are more likely to be placed in special education than girls and there is some evidence that the effect of school starting age on special education identification is larger for boys in the early years (Dhuey & Lipscomb, 2010) particularly for emotional impairment, autism spectrum disorder, and specific learning disability placements (Dhuey et al., 2019). Few studies have estimated heterogeneity by race or socioeconomic status on ADHD diagnosis, but there is some evidence of a larger effect of school starting age on special education identification for White students (Dhuey et al., 2019; Dhuey & Lipscomb, 2010). In light of the large literature on disproportionality in special education receipt by race and socioeconomic status, more evidence is needed to understand the interaction between demographic characteristics and disability identification.

In contrast, there has been very little research into heterogeneity in the effect of school starting age on special education identification within states, despite the large role that local school districts play in setting special education policies. For example, states and localities have significant control over designing the referral and evaluation process, which a recent Government Office of Accountability report found contributes to the variation in the percent of students served in special education across states (2019). States also vary in which professionals are required to participate in diagnosis for each disability type (e.g., MacFarlane & Kanaya, 2009), which age ranges can qualify for a developmental delay diagnosis, and how to identify specific learning disabilities. Underlying this cross-state variation in referral practices, local education agencies are similarly able to adapt their policies to the state guidance and often produce guidance for local agencies to clarify state policy (Staskowski, 2006). Therefore, we might expect that the school district in which a child is enrolled would impact their likelihood of being placed in special education due to their school starting age.

Why are younger students more likely to be diagnosed with a disability?

Both the literature on age effects for ADHD and special education identification support the conclusion that the youngest students in a grade cohort are more likely to be placed in special education, but less is known about why this might be the case. Nevertheless, prior work has presented a number of hypothesized mechanisms to explain disparities in special education identification attributable to the special education evaluation process. In particular, some have hypothesized that the use of peer-to-peer comparisons to inform referral practices likely exacerbates disproportionate identification rates for the youngest students. For example, younger students could be more likely to be referred to special education because age-typical developmental differences are attributed to signs of disability while older students are less likely to be referred because developmental delays are masked by an age premium when compared to their younger peers. If this is the case, the age of students in relation to their peers, rather than their absolute age may be driving differences in special education identification rates.

Peer comparisons are likely to play a large role in special education because the referral and evaluation process relies on parents, teachers, and other education and health professionals to identify and flag signs of disability that may be impacting a child's learning.[1] A number of studies on teacher referral practices, both in special education and gifted and talent education, have found that teacher experience, sense of self-efficacy, and gender-, race-, and ethnicity-related biases impact referral choices (Grissom & Redding, 2016; Klingner & Harry, 2006; Skiba et al., 2006). Although the percent of referrals initiated by teachers is not widely reported, teacher referrals likely make up a large proportion of total special education referrals for school-age children. Thus, we might expect that many special education referrals are based on evaluation criteria derived from peer-to-peer comparisons in a specific school or classroom (i.e., comparing children's development to the development of the other children in their "frog pond" (Davis, 1966)) and teacher beliefs about a student's ability to be successful in general education (Dunn, 2006).

In fact, peer group comparisons have been found to impact how teachers assess a child's academic performance through grading practices (Farkas, Sheehan, & Grobe, 1990) and who is referred for special education evaluation (Hibel et al., 2010). More specifically, Hibel and co-authors tested the effect of peer groups on likelihood of special education identification by comparing students with the same test scores, finding that those with high-performing peer

[1] After a student is referred for services and the parent gives consent for evaluation, schools have 60 days to complete an evaluation design an Individual Education Plan for students found eligible for services. Many states then require the use of standardized developmental assessments in making eligibility determinations (Michigan Department of Education, 2016). States are also required to have Child Find programs to identify children who may be eligible for services but have not started school yet under Part C of the Individuals with Disabilities in Education Act (2004)

groups were more likely to be referred for special education services than those with a lower-performing peer group (Hibel et al., 2010). Similarly, special education disparities by race can be impacted by peer group composition, with minoritized students with the same achievement scores more likely to be placed in special education in predominately White schools but less likely in predominately non-White schools (Elder et al., 2019).

Particularly in early grades, when performance on academic measures and age are highly correlated, we might expect that the youngest children are more likely to be referred to special education because teachers have age-inappropriate expectations for skill acquisition and classroom behavior for the youngest children. Special education referrals based on peer comparisons are also more likely to be biased towards younger children in the early grades because child development is occurring rapidly and there will be noticeable but age-typical biological and cognitive differences between students who are a year apart in age because of their entrance age eligibility (Brown & Jernigan, 2012). Thus, expecting that all students reach the same developmental benchmarks together in a grade may lead teachers to be more likely to flag the youngest students as developmentally delayed even if their development falls within age-appropriate expectations.

Present Study

Drawing on the nascent literature estimating the effect of school starting age on special education identification and the hypothesis that these effects are caused by relative age differences that favor the referral of the youngest students, I address three research questions:

1. What is the effect of being young for grade on special education service receipt in each year of elementary and middle school in Michigan?

2. Are these effects heterogeneous by gender, race/ethnicity, or economic disadvantage at kindergarten entry?
3. Does the impact of being eligible to be the youngest student in a grade on the likelihood of special education identification vary across intermediate school districts (ISDs) or school districts in Michigan?

I also test for evidence that these effects are driven by relative age rather than absolute age using a unique source of variation in classroom age ranges due to kindergarten enrollment policies in Michigan.

Michigan is an interesting context in which to study this question for several reasons. First, children in the same kindergarten classroom can range from 4.75 years old to 6.75 years old at the start of school due to kindergarten enrollment policies.[2] Thus, the "normative standard" of skill acquisition and classroom behavior that a teacher uses to make special education referrals may be inappropriate for both the youngest and the oldest children in a grade, who can be two years apart in age on the first day of school. Second, although Michigan's overall special education rate is close to the national average, students in Michigan are much more likely to be placed in special education with a speech or language impairment in the early grades (67% in Michigan compared with 44% in the US), making the state an outlier in disability classification practices (NCES, 2017). Finally, Michigan is regionally and demographically different from Florida, the other state in which this question has been explored in depth, despite having a similar overall special education rate. For example, Michigan's public school population is roughly 70% White, 20% Black and less than 10% Hispanic, whereas Florida's is 37% White,

[2] Students are eligible to start kindergarten between the ages of 4.75 and 5.75 during the study period. However, some students choose to delay entry and others repeat kindergarten, making them between 5.75 and 6.75 years old on the first day of school.

22% Black, and 34% Hispanic. Thus, the present study allows for an exploration of whether the findings in Florida are replicable in a different context.

Method

Sample

The current study uses data from the Michigan Education Data Center (MEDC) which houses the state administrative education data collected by the Center for Educational Performance and Information (CEPI) at the Michigan Department of Education (MDE). The study sample includes all first-time kindergarten entrants between school years 2002-2003 and 2012-2013 who enrolled in a Michigan public school, including both traditional and charter schools. During this period, entering kindergarten cohorts ranged from 120,000 in the earlier cohorts to 110,000 students in the later cohorts for an overall sample of 1,285,165 students over ten years. I exclude 17,822 students (1.4%) without available birthday information and 592 students whose birthdays were implausible and likely to be data entry errors (<0.01%). I follow all first-time kindergarten enrollees for five follow-up years after kindergarten eligibility (5^{th} grade for most students) and for eight follow-up years (8^{th} grade for most students) for cohorts one through seven.

I also exclude students who entered the public schools in later grades because I cannot observe whether these students started kindergarten on time nor what their special education status was prior to entering the Michigan school system. Excluding students who don't start kindergarten in a Michigan public school limits the sample to approximately 85% of all students in grades 1-8[3]. My study sample of first-time kindergarten entrants is 49% female, 68% White,

[3] There are a number of reasons a students may not have enrolled in kindergarten but did so in elementary school. Some students will have moved into Michigan from another state while others may enrolled in a private kindergarten program. Additionally, kindergarten is not mandatory in Michigan though in recent years an estimated 95% of students have enrolled in kindergarten before starting first grade (Chambers, 2019)

20% Black, 7% Hispanic, 3% Asian, and 1% Asian. Approximately 42% of students qualified for free or reduced price lunch in their kindergarten school year (at or below 185% of the federal poverty line) and nearly 7% were considered limited English proficient in kindergarten. The study sample is nearly identical to the full population of K-12 students on these demographic measures in Michigan during this time period (result available upon request).

Identification strategy

Until the 2012-2013 school year, which is the latest cohort included in the study sample, a child who turned five years old on or before December 1st was eligible to enroll in kindergarten in the fall of that school year (Public Act 451, 1976). A child who turned five years old on or after December 2nd was required to wait until the following fall to enroll in kindergarten. By establishing a cutoff determining which students were eligible to start kindergarten in each year, the kindergarten entrance policy effectively sorts those students who turn five on the days leading up the cutoff and the days just after the cutoff into two conditions. The first, which I refer to as the treatment condition, is being the youngest student in a given grade cohort. Those students born on December 1st were eligible to start kindergarten at approximately 4.75 years old with peers their exact age or older. The second condition, which I refer to as the control condition, is being the oldest student in a given grade cohort. Those students born on December 2nd would not be eligible to start kindergarten until the following fall when they were approximately 5.75 years old with all peers their exact age or younger.[4]

Although the Michigan kindergarten entry law stipulates at what age children are eligible to start kindergarten, not all students who were eligible to enroll did so. There are two primary avenues for parents to modify the kindergarten enrollment of their children. The first is by

[4] School years in Michigan typically start on the first Tuesday after Labor Day, so age on the first day of school may vary by a few days across years.

choosing to delay starting school. The compulsory attendance law in Michigan does not require children to be enrolled in school until the year they turn six, meaning that parents of children born just before the kindergarten cutoff can choose to delay enrollment until the following school year and still be in compliance with Michigan law. Parents who delay their child's school entrance, a practice often called "redshirting," make their children among the oldest students in their grade even if they were eligible to enroll in kindergarten as the youngest students. During the study period, approximately 5% of all students were delayed entrants consistently across cohorts with those who turned five in the 30 days before the cutoff date the most likely to redshirt (15-18% across cohorts).

In a related practice, some school districts in Michigan offered a developmental kindergarten program during this period, giving children who would be the youngest students in their grade, or who are not yet eligible for kindergarten, the opportunity to enroll in a two-year kindergarten sequence. The first year of the program, often called "Young Fives," is intended to ease children into school settings before enrolling in a traditional kindergarten class in the second year. Given the two-year structure of the program, the students who participate in Young Fives become the oldest students in their grade during the second year of the program. Using the administrative program code for developmental kindergarten, 5-7% of students were enrolled in a developmental kindergarten program in their first kindergarten year. During this period there was little way for the oldest eligible students to enroll early.[5]

[5] Under the new September 1st cutoff established in the 2015-2016 school years this has changed. Early entrance waivers allow children who are not eligible to start K based on the cutoff date to enroll early if they turn five between September 2nd-December 1st and are granted an early entrance waiver at the parents' request. Developmental kindergarten programs have also become more popular during this period.

Special education policy in Michigan

Special education policy in Michigan is set by the Michigan Department of Education, but implemented by two smaller administrative units, the Intermediate School District and the local school district. In my study period there were 57 Intermediate School Districts (ISDs) which are structured as separate taxing units that provide administrative and instructional services to their member local school districts and charter districts (Michigan Association of Intermediate School Administrators, 2020). The ISDs provide a number of special education services to their member districts to ensure compliance with federal disability law, provide professional development for special educators, and promote efficient allocation of expensive but low-incidence programs. Many ISDs also operate buildings that directly serve students with disabilities. Specific approaches to special education can vary by ISD depending on available resources and preferred approaches to providing special education services. For example, some districts operate separate classroom programs for students with disabilities in the early grades while other districts offer few disability specific programs (Personal Communication, Lisa Wasacz, March 24, 2019). For this reason, there may be policy-generated variation in the effect of school starting age on special education identification across ISDs.

Underneath the Intermediate School Districts, during my study period there were between 553-548 local school districts ranging in size from large urban districts (N = 35) to small rural districts (N = 285) with the largest district serving 67,064 students in 2012 and the smallest serving fewer than 100 students in 2012. The ISDs also include public school academies or charter school agencies that can run multiple school buildings. During this period the number of charter school districts increased from 180 in 2002 to 260 in 2012. Although the ISDs are often responsible for setting special education guidelines for their member school districts, differences in student populations, teacher experience, and availability of resources may also contribute to variation in the effect of school starting age within ISDs.

Outcomes

The primary outcome of interest is special education identification as measured by having an Individualized Education Plan (IEP). I measured special education participation as a binary indicator for whether a child had an IEP in their first kindergarten eligible year and each subsequent follow-up year set to 1 if the child has an IEP and 0 otherwise. I also constructed a binary indicator for ever being placed in special education set to 1 if the child ever had an IEP in any year he or she was enrolled in a Michigan public school.

In addition to measuring special education receipt, I constructed measures of special education exit and special education reentry. Special education exit is a binary indicator set to 1 if a student had an IEP in a given year and no longer had an IEP in subsequent years, conditional on still being enrolled in a Michigan public school. Similarly, special education reentry is a binary indicator set to 1 if a student had an IEP in a given year, did not have in IEP in a subsequent year, and then again had an IEP in a subsequent year. The reentry measure is also conditional on still being enrolled in MI public school during those years. I also constructed measures of the percent of years enrolled in Michigan schools with an IEP and total number of years of service receipt as a measure of the duration of time spent in special education during Michigan public school enrollment.

Finally, I constructed a binary indicator for the primary disability associated with each student's IEP in a given year. All students with IEPs have a specified primary disability which groups students into broad categories based on service need and disability diagnosis under the guidance of the Individuals with Disabilities in Education Act (2004). I further grouped some disability categories that are low-incidence to generate the following disability categories: Intellectual impairment, speech and language impairments, specific learning disability, developmental delay, autism spectrum disorder, emotional impairment, and physical/severe impairment.[6] For all measures described above, the indicator is set to missing if the student is not enrolled in a Michigan public school for that school year.

Predictors

Running variable. The kindergarten cutoff law creates a policy-generated discontinuity in the likelihood that a child will enroll in kindergarten as the youngest in their cohort. The variable that sorts children into either treatment or control at this cutoff (i.e., the running variable) is a child's birthday. Using student birthday, I construct the running variable as a measure of days between the child's fifth birthday and the December 1st cutoff. I center the variable to have a value of 0 on December 1st so that children born in the 182.5 days before the cutoff have negative values of the running variable and children born in the 182.5 days after the cutoff have positive values.

Eligibility indicator. The eligibility indicator is a binary indicator of whether a student was eligible for kindergarten entrance at a younger age. Students born between June 1st and the December 1st cutoff are eligible to start kindergarten in the younger half of the age range (between 4.75 and 5.25 years old) and have an eligibility indicator set to 1. Students born after December 1st and before June 1st are eligible to start kindergarten in the older half of the age range (between 5.25 and 5.75 years olds) and have an eligibility indicator set to 0.

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[6] Physical/severe impairment includes orthopedic, hearing/visual impairments, deaf-blindness, traumatic brain injuries, and severe multiple impairments in the primary specifications. I also constructed a measure of physical impairment without traumatic brain injuries and severe multiple impairments, both of which can be related to cognitive impairments as well, to test the robustness of my disability specific estimates to my choice to combine physical and severe classifications.

Enrollment indicator. As described above, not all students who are eligible for kindergarten each year enroll. Thus, whether a student enrolled in kindergarten at the youngest eligible age is partially endogenous due to selection into enrolling on time. Therefore, I construct a binary indicator for young enrollment set to 1 if a student enrolled in kindergarten between 4.75 and 5.25 years old).

Covariates. I also include measures of time-invariant or pre-treatment student characteristics in all primary specifications. These include binary indicators of gender and race and ethnicity as reported in the state-level administrative data (Asian, Black, Hispanic, White, and Other), socioeconomic status as measured by eligibility for free or reduced price lunch, receipt of special education services through public preschool or Early On (Michigan's early intervention program), and immigrant status. In addition to using these characteristics as controls in the main impact models, I use these covariates to estimate subgroup effects by gender, race/ethnicity, and socioeconomic status.

Data Analytic Strategy

To estimate a causal relationship between a child's age at time of school entry and the likelihood they are placed in special education, I used a natural experimental design called a regression discontinuity. In this study context, the running variable is a child's age (as measured by their birthday) which orders children by age, and the cutoff is the December 1st kindergarten entry policy which determines if a child's age will be the youngest or the oldest in a given kindergarten cohort. Thus, the kindergarten cutoff policy creates an exogenous source of variation in the likelihood that a child is the youngest student in her grade cohort which allows for a causal interpretation of the effect of being the youngest student on the likelihood of special education receipt. The December 1st kindergarten cutoff in Michigan has been used in regression discontinuity approach to evaluate intent-to-treat effects of eligibility age at kindergarten entry on high school graduation, academic performance in high school, and postsecondary enrollment and persistence in a previous study (Hemelt & Rosen, 2016). In the present study, I estimate both the effect of being *eligible* to be the youngest student in a grade (i.e., the intent-to-treat effect) and the effect of *enrolling* in kindergarten as the youngest student in grade (i.e., the local average treatment effect).

I use a sharp regression discontinuity to estimate an intent-to-treat effect of being eligible to start kindergarten as the youngest student in a grade cohort on the probability of being placed in special education in kindergarten and each follow-up year. Equation 1 is the estimation equation for the intent-to-treat effect of being the youngest in grade, where *Y* is the outcome of interest for child *i* in cohort c, *Elig* is a binary indicator for whether child *i* is eligible to enter K at a young age in cohort c, *Cutdist* is the distance in days between child *i'*s fifth birthday and the December 1st cutoff in cohort c, X' is a vector of time-invariant or pre-treatment student characteristics for student *i* in cohort *c,* γ is a vector of cohort fixed effects and ε_{ic} is the student-level error term. The student characteristics are student gender, race and ethnicity, free and reduced price lunch status, immigrant status, and prior receipt of special education services in prekindergarten or before. I also cluster the standard errors at the kindergarten enrolling district to account for potential correlation of the error term among students enrolled in the same school district.

$$Y_{ic} = \beta_{ic} + \alpha(Elig)_{ic} + \sigma(cutdist)_{ic} + X'_{ic} + \gamma_c + \varepsilon_{ic} \qquad (1),$$

Figure 1 plots the relationship between the running variable and the likelihood of entering kindergarten at a young age. If the cutoff date were completely deterministic, we would expect to see all students on the right side of the cutoff with a 100% probability of enrolling at a young age and all students on the left side of the cutoff with a 0% probability of enrolling at a young age. However, although I find a large discontinuity in the likelihood of entering kindergarten at a young age at the cutoff, Figure 1 demonstrates that the probability of young enrollment decreases from 100% as student birthdays approach the December 1st date. For this reason, I also use a fuzzy regression discontinuity design to account for imperfect compliance with the eligibility criteria where eligibility for kindergarten entry at a young age is used as instrument for enrolling.

More specifically, I use a two-stage least squares approach in which I first estimate the probability that a child enrolls in kindergarten at a young age based on their eligibility to do so. The first stage equation (2) has the same terms as the intent-to-treat equation (1) with the exception of the outcome, which is the probability of enrolling in kindergarten at a relatively young age.

$$Enroll_{ic} = \beta_{ic} + \alpha(elig)_{ic} + \delta(cutdist)_{ic} + X'_{ic} + \gamma_c + \varepsilon_{ic} \qquad (2),$$

I then use this predicted probability of young enrollment to estimate the local average treatment effect of being young for grade on the outcomes of interest (Y_{ic}) the second stage, where α is the parameter of interest.

$$Y_{ic} = \beta_{ic} + \alpha(\widehat{enroll})_{ic} + \sigma(cutdist)_{ic} + X'_{ic} + \gamma_c + \varepsilon_{ic} \qquad (3),$$

For both the ITT and LATE estimating equations, I use a non-parametric local polynomial model that uses only those observations just around the cutoff to estimate the relationship between the running variable and the outcome of interest on either side of the cutoff. Following the literature, I use a data-driven selection mechanism to select a bandwidth of observations that optimizes the bias-variance tradeoff associated with using only those observations closest to the cutoff versus including observations farther from the cutoff (Skovron & Tituinik, 2015). Based on graphical evidence of the relationship between the outcome variable and the running variable, I use a linear functional form to select the bandwidth and to estimate the effect of being young for grade. Finally, I use a triangular kernel that assigns the greatest weight to observations closest to the bandwidth with the weight decreasing linearly as observations get farther from the bandwidth. For all procedures described above, I use the *rdrobust* package in Stata.

Student-level heterogeneity

To answer the second research question — Are these effects heterogeneous by gender, race/ethnicity or economic disadvantage at kindergarten entry? — I use the same regression discontinuity approach, fitting the primary specification for both the ITT estimates (equation 1) and the LATE estimates (equations 2 & 3) separately by gender, race and ethnicity, and socio-economic status (free or reduced price lunch eligible), using the subgroup relevant bandwidth and functional form. I then plot the estimated effect and corresponding robust confidence intervals for each subgroup to compare the magnitude and precision of the estimates. I also conduct sub-subgroup analyses to explore the possibility that gender differences vary across racial groups. To date, there is no widely accepted approach to testing the statistical significance of the difference in subgroup estimates using the local polynomial modeling approach (Carril, Cazor, Gerardino, & Litschig, 2018). For this reason, I compare the magnitude of the estimates to make inferences about the potential for heterogeneity in effects but do not interpret the findings as confirmatory evidence.

Estimating the distribution of intent-to-treat effects across sites

To answer the third research question — Does the effect of school starting age vary across intermediate school districts (ISDs) or school districts in Michigan? —I quantify the distribution of these intent-to-treat effects across the two administrative units using the framework described by Bloom et. al (2017) and applied by Weiss et. al. (2017) and Unterman and Weiland (2019). To date, this approach has only been applied to estimate variation in intent-to-treat estimates in randomized control trials, so I limit these analyses to the intent-to-treat analysis as well. Because the statewide cutoff is applied universally across governance units, a student who is eligible to be the youngest student in the statewide cohort is also eligible to be the youngest student in her ISD, in her school district, in her school, and in her classroom. Therefore, I consider the ISDs and school districts to be study sites nested within the broader state population. This conceptualization mirrors prior literature using this approach to estimate variation in treatment effects in multi-site randomized control trials (Bloom et al., 2017).

I first estimate an intent-to-treat effect for each site, β_j, (i.e., each ISD and each school district) and then estimate a grand mean effect (β) and the cross-site standard deviation of the distribution of these site-specific effects (τ). Following the approach of Weiss et. al., (2017) and Unterman and Weiland (2019), I use a two-level hierarchical linear model to estimate parameters β and τ where level 1 is at the student-level and level 2 is at the relevant site level. In equation 1, Y_{ij} is the outcome for child *i* from district *j*, $district_{ij}$ is equal to one if child *i* enrolled in district or ISD *j*, T_{ij} equals one if child *i* was assigned to treatment and zero otherwise in district *j*, X_{lij} is a vector of baseline covariates and cohort fixed effects (Equation 4). Because the identification strategy in this context is a regression discontinuity, I also include the running variable $cutdist_{ij}$ in the level 1 equation and restrict the analytic sample to the same bandwidth of students as in the primary RD specifications for a given outcome.

Level 1 (Individuals):

$$Y_{ij} = \sum_{r=1}^{R} \alpha_j \, District_{ij} + \mathrm{B}_j T_{ij} + \theta cutdist_{ij} + \sum_{l=1}^{L} \gamma_l X_{lij} + e_{ij}$$

Level 2 (Sites)

$$B_j = \beta + b_J \tag{4}$$

The two-level model described above has site-specific fixed intercepts and site-specific treatment coefficients that can vary randomly across sites. The site-specific fixed intercepts account for the possibility of differing proportions of students in the treatment and control groups in each site. The site-specific treatment coefficients, B_j, are modeled as representing a cross-site population distribution with a mean value of β (i.e., the grand mean ITT effect) (equation 5) and a standard deviation of τ (equation 6). Using this approach, the residual error term b_J has a mean value of 0 and a standard deviation of τ and the individual level error term e_{ij} is assumed to have a mean of zero and a variance of $\sigma^2{}_{|\text{site}}$ that is allowed to differ between the treatment and control groups. To test for statistical significance of τ I use a chi-square test on a Q statistic, which is widely used in meta-analysis of heterogeneity in treatment effects (Hedges & Olkin, 1985). For further information about this approach see Bloom et. al (2017).

$$\beta = \frac{\sum_{j=1}^{J} B_j}{J} \tag{5}$$

$$\tau = \sqrt{\frac{\sum_{j=1}^{J} (B_j - \beta)^2}{J}} \tag{6}$$

Results

Effect of school starting age on special education identification (RQ 1)

In the full 5th grade follow-up sample, students who are eligible to enroll in kindergarten at the youngest age are 2.8 percentage points (p<0.001) more likely to be receiving special education services in kindergarten (Table 1). Further, this effect persists in both magnitude and direction through the fifth follow-up year when most students would be in fifth grade. This suggests that the initial higher identification rates of students eligible to enroll at the youngest age in kindergarten are not balanced by higher identification rates of the oldest students in subsequent grades. The effect of enrolling in kindergarten as the youngest student in the class is 3.3 percentage points ($p<0.001$), which is a 40% increase in the likelihood of placement. Again, this effect persists through the fifth follow-up year in direction, decreasing slightly to 2.7 percentage points (Table 2). The magnitude, direction, and pattern of effects is similar in the 8th grade sample (Appendix, Figure A.3, Table A.2).

In addition to estimating the effect of being young for grade on special education service receipt in each follow-up year, I also estimate the overall effect on ever receiving services from kindergarten through elementary (for the fifth grade sample) and middle school (for the eighth grade sample) to align with the prior literature (Dhuey et al., 2019). I find that students who are eligible to be the youngest in grade are 3.7 ($p<0.001$) percentage points more likely to ever receive special education services. Students who enroll as the youngest in grade are 4.3 percentage points ($p<0.001$) more likely to receive services. They are also 2.2 percentage points more likely to exit special education after starting to receive services although there is no statistically significant difference in the percent of time spent in special education between the treatment and control groups (Table 3). Finally, following the prior literature, I estimated the effect of being young for grade on special education placement for specific primary disability categories. I find that the majority of the effect in kindergarten is concentrated in the more subjective classification of speech/language impairment. This is not surprising given that over 75% of all kindergarten students with IEPs have a primary disability diagnosis of speech or language impairment (results available upon request).

Variation by student characteristics (RQ 2)

Overall, the percent of students with IEPs in kindergarten varies by gender, with 14% of boys in special education compared with 7% of girls. White students are also slightly more likely to have IEPs (11%) than Black and Hispanic students (9%) as are students who qualify for free/reduced price lunch (12% versus 9%). For this reason, I present the subgroup estimates in effect sizes rather than percentage points by dividing the percentage point differences between the treatment and control group by the standard deviation of the control group mean. As previously described, I do not test whether the estimated effects are statistically significantly different from each other but rather plot the estimated effects and their confidence intervals to compare magnitudes and direction.

Figure 3 shows the LATE effect of being young for grade for boys and girls in the first kindergarten eligible year and five following years. Although the estimated effect in percentage point differences is twice as large for boys as girls in kindergarten (4.4 percentage points for boys (p<0.001) compared with 2.2 percentage points for girls (p<0.001), the effect sizes are more similar in magnitude (0.14*sd* versus 0.10*sd*). In years one through five, the effect of school starting age is similar in magnitude for boys and girls, with the exception of follow-up year 3 when the effect for girls is half that for boys. The results do not suggest meaningful heterogeneity in the effect of being young for grade on special education identification by gender.

Figures 4 and 5 plot the estimated relative effects in effect sizes by race/ethnicity and socioeconomic status respectively. There is no evidence that the effect of school starting age is heterogeneous by race/ethnicity though the magnitude of the effects appears to be largest for White students in the early grades. In contrast, the effects appear to increase in magnitude for

Black and Hispanic students in the later years although the confidence intervals for all three race group estimates overlap. The effect is also similar in magnitude for students who do and do not qualify for free and reduced price lunch although it may be somewhat larger in magnitude in the early years for students who do not qualify for free or reduced price lunch. For all subgroups, being young for grade increases the likelihood of being in special education (see Appendix, Table A.5 for point estimates).

Although there is no clear evidence of heterogeneity by race/ethnicity for the full sample, I also estimated heterogeneity in the interaction between gender and race. Figure 6 shows the percent of young students in special education in kindergarten through 5th grade in comparison to their older peers for White and Black girls and for White and Black boys at each time period. The estimated effect of school starting age for White boys is more than double that for White girls in kindergarten and remains larger through the fifth follow up year. In contrast, the estimated effect for Black boys and Black girls is similar in magnitude in kindergarten but increases to triple the magnitude for girls as for boys in the fifth follow up year. In fifth grade, young White boys are 4 percentage points more likely to be in special education than older White boys whereas young Black girls are 6 percentage points more likely to be placed in special education than young Black girls.

Variation across school districts (RQ 3)

Figures 7 and 8 illustrate the distribution of the intent-to-treat effects on kindergarten special education identification and ever being placed in special education through follow up year five across Intermediate School Districts (ISDs). In both cases, the estimated grand mean difference is positive and similar in magnitude to the estimate using the primary regression discontinuity specification. Although I detected a statistically significant grand mean effect on the likelihood of kindergarten special education identification, the $\hat{\tau}$ is smaller than 0.001 percentage points and statistically significant at the $p<0.05$ and $p<0.001$ levels respectively. Simply put, the standard deviation of the distribution of site-specific treatment effects is statistically significant and very small, providing no evidence of heterogeneity in effects across ISDs. I find similar results at the district level (Appendix Figures A.4 and A.5).

Robustness Checks

I also conducted a series of internal validity and robustness checks following the guidance of the What Works Clearinghouse (2017) and prior literature to test the credibility of a causal interpretation of my findings. First, I assessed the likelihood that parents could influence either the cutoff itself or their position along the running variable in response to the cutoff using contextual information, statistical tests, and graphical evidence. Contextually, there is little reason to think that parents could have influenced the cutoff itself, which was a statewide policy dating back to 1979 (Public Act 451, 1979). It is also implausible that parents could or would plan their child's birthday to fall right at the cutoff. Although there is evidence of selection of birth in particular seasons that correlates with demographic characteristics (Bound & Jaeger, 1996) it is unlikely that parents could *precisely* plan their child's birthdate to fall within a few days of the cutoff. In fact, only an estimated 5% of babies delivered through natural child birth are born on their due dates and human gestational lengths can range up to 5 weeks making it difficult to choose an exact date of birth at conception (Jukic et al., 2013). There is also little incentive to manipulate a child's birthday right around the cutoff in this context; parents who do not want their child to enroll in school at the youngest possible age can simply choose to delay kindergarten entry until the following year.

Although contextual evidence suggests a minimal threat of manipulation to the running variable, I used graphical and statistical tests to assess whether there is smooth variation of the running variable through the cutoff. I used both the McCrary density test, which uses a local linear estimator (McCrary, 2008), and the *rddensity* test, which uses a local cubic estimator with quadratic bias correction (Cattaneo, Jansson, & Ma, 2018) to test for evidence of discontinuous density of observations on either side of the threshold. I find no evidence of a statistically significant difference in the density of observations through the cutoff. Graphically, I used a local quadratic estimator to plot the density of the running variable at each value on either side of the cutoff. Again, I find no visual evidence of manipulation of the cutoff (Appendix, Figure A.1). I also find no evidence of discontinuities in pretreatment characteristics around the cutoff (Appendix, Table A.1). Neither the average impacts nor subgroup impacts are sensitive to how the bandwidth is selected (Appendix, Table A.4) nor to functional form (results available upon request). Similarly, the estimated cross-site distribution is robust to using four data-driven bandwidths for both the ISD and district-level analyses (Appendix Table A.5).

I tested for evidence of biasing overall and differential attrition following the guidelines for assessing attrition in regression discontinuity designs from the What Works Clearinghouse (2017). Using the same linear functional form and bandwidth selector as the primary specification, I predicted the probability of having missing values on the special education outcomes at the cutoff on each side, and then estimated the difference between these two intercepts. The overall and differential attrition rates for the special education outcomes in follow-up years 1-5 for the full 5th grade sample fall within the range of tolerable threat of bias under both cautious and optimistic assumptions. I also compared the pre-treatment covariate characteristics of those with missing data at each time period in the treatment and control groups.

I find that students with missing data in the second follow-up year are more likely to be Black by 10.5 percentage points (0.25*sd*) and students with missing data in the third follow-up year are less likely to be White by 12 percentage points (0.25*sd*) but otherwise the estimated differences are small in magnitude (Appendix Table A.6).

Finally, I conducted two falsification tests. First, I generated 24 pseudo-cutoffs at two randomly selected dates in each month and tested for a discontinuity in the outcome variables at each of those dates. I find no evidence of a discontinuity at any point other than the true cutoff (Appendix, Figure A.2). I also conducted a falsification test similar to those used in the ADHD diagnosis literature (Layton et al., 2018) using special education classifications unlikely to effected by school starting age. I estimated the effect of being young for grade on the likelihood of having an IEP for a physical or severe impairment (i.e., orthopedic, hearing/visual impairments, deaf-blindness, traumatic brain injuries, and severe multiple impairments) or for a physical impairment alone (i.e., orthopedic, hearing/visual impairments, deaf-blindness). I find no evidence of an effect of school starting age in kindergarten through 8th grade on likelihood of physical/severe disability classifications or physical disability classifications alone. In comparison, I find an effect similar in magnitude and direction to the average effect for receiving services for speech or language impairment, a classification that is more subjective (Appendix, Figure A.6)**.**

Mechanisms

My findings that the students who are the youngest in their grade are more likely to be identified for special education services are consistent with prior literature (Dhuey et al., 2019; Dhuey & Lipscomb, 2010; Elder, 2010; Layton et al., 2018). As many have noted, however, the youngest students are not just younger than their peers in terms of relative age. They are also younger in absolute age, which could have an effect on the incidence of developmental delays that require special education. Conversely, the oldest students in a grade are a least a year older than their youngest peers, which has been found to explain much of the positive effect of being old for grade on test scores and could explain a lower incidence of developmental delays for older children (Black, Devereux, & Salvanes, 2011; Deming & Dynarski, 2008). As in the prior literature, I cannot disentangle whether the present study findings should be interpreted as a relative age effect, an absolute age effect, or a combination of the two. However, using variation in cohort age composition across schools, I conducted an exploratory analysis to estimate heterogeneity in the effect of school starting age for students in schools with particularly narrow or particularly wide kindergarten cohort age distributions. In other words, I estimated the effect of school starting age for students who begin school at the same absolute age in both the treatment and control groups, but who are of different relative ages because of their peers' school starting age. Though descriptive, this approach considers how relative age may be associated with the effect of school starting age on special education independently of absolute age.

In Michigan, the age ranges of kindergarten cohorts vary considerably across schools due to differential patterns of redshirting and inconsistent developmental kindergarten program offerings across the state. In schools with wide age ranges, the youngest students born on December 1st may have many peers who are a year or even two years older than them. In schools with narrow age ranges, the youngest students may have fewer peers who are substantially older than them. Although an individual's choice to redshirt or enroll in developmental kindergarten may be endogenous to their likelihood of special education placement, I argue that peer age composition is plausibly exogenous for on time enrollees because parents who enroll their children on time cannot choose whether their child's peers delayed entry, shifting their child's relative age position as a result. However, because the characteristics of the schools that students enroll in for kindergarten are neither time-invariant nor measured prior to kindergarten eligibility, I consider these analyses exploratory.

Based on the distribution of the standard deviation of the mean age (σ^2) in each school-grade-cohort across my sample period, I constructed two groups[7]. Students in the high variance group were those who enrolled in a school where the kindergarten grade was in the upper quartile of the distribution of ages across the state (σ^2>=0.42), which is approximately 25% of students in the control group and 33% of students in the treatment group. Students in the low variance group were those who enrolled in a school where the kindergarten grade was in the bottom quartile of the distribution of ages across the state (σ^2<=0.33), which is around 22% of the control group and 25% of the treatment group.

Visually, there is a clear discontinuity in the likelihood of being placed in special education in kindergarten around the cutoff for students who were eligible to enroll in kindergarten at a relatively young age in high variance schools. In contrast, there is no clear discontinuity in the likelihood of special education identification around the cutoff for students in low variance schools (Appendix Figure A.7). Using the primary specification from the main analysis, I find that students who enrolled in kindergarten at a young age in a high variance school are 10.7 percentage points more likely to be identified for special education services in kindergarten than their older peers (p<0.001 ES=0.32). In contrast, I find no differences in the likelihood of identification in low variance schools. Similarly, the youngest students in high variance schools for kindergarten are 9.12 percentage points (p<0.001, ES= 0.21) more likely to

[7] In my study period, the mean starting age of kindergarten cohorts within a school ranged from 5.17 years to 5.62 years old. The standard deviation of starting ages ranged from 0.29 years to 0.55 years. Thus, in the most extreme cases there were schools with the majority of kindergarteners starting between 4.9 – 5.5 years old and schools with the majority of students starting between 5 – 6.2 years old.

ever be placed in special education in K-8. I find no statistically significant differences in the likelihood of ever being placed for students who enrolled in kindergarten in low variance schools (Table 4). I also conducted these analyses using four age groupings, where the high and low variance schools were each split into high and low mean subsets and find the same pattern (results available upon request).

Although exploratory, these findings indicate that higher rates of identification for the youngest students may be related to teachers or other referrers having difficulty distinguishing developmental differences across ages. Particularly in the early grades when development progresses quickly (Hill, Bloom, Black, & Lipsey, 2008), teachers may find it particularly difficult to differentiate between typical differences in development for children who are over a year apart in age. In classrooms with relatively narrow age ranges, teachers may be less likely to see large developmental differences among peers and therefore less likely to recommend the youngest children to special education programs. These exploratory results are also informative for interpreting the null results from the cross-district analysis. Although I find no discernable differences in the effects of school starting age across school districts or ISDs, these findings suggest heterogeneity in effects by school peer composition within school districts.

Discussion

Students who are eligible to attend kindergarten at the youngest possible age are nearly 40% more likely to be placed in special education in kindergarten as those who are eligible at the oldest possible age (3.3 percentage points, or 0.12 *SD*). These students are also more likely to be in special education programs through 8^{th} grade, meaning that the initial age effect is not balanced by compensating higher identification rates for older students in later grades. My findings align with those found in the prior literature, and are similar in magnitude to the most recent evidence from Florida (Dhuey et, al., 2019). They also fill a gap in the literature by estimating the effect of school starting age at each year from kindergarten entry through the end of middle school rather than just in the early grades (Dhuey & Lipscomb, 2010) or ever during schooling (Dhuey et. al., 2019).

I find little evidence that the effect of school starting age is heterogeneous by gender, race, or socioeconomic status. However, I find exploratory evidence that the age effect is particularly large for White boys in the early grades and for Black girls in the later grades. These within race gender effects have not been explored in the prior literature and raise new question for future research. Overall, the effect of school starting age on the likelihood of receiving special education services is positive for all subgroups explored in the present study. Finally, I find no evidence of cross-district variation in the intent-to-treat effect of being young for grade on special education identification in kindergarten or ever from kindergarten to eighth grade. The present study is the first of my knowledge to estimate heterogeneity in the age effect across school districts, with the implication that district-level policies do not moderate the average effect of school starting age. I also find support for interpreting these effects as primarily driven by relative age rather than absolute age differences between the oldest and youngest students, supporting the theory that comparisons of development across age biases special education identification towards the youngest students (Dhuey et al., 2019; Elder, 2010; Hibel et al., 2010; Layton et al., 2018).

These findings have several implications for special education policy, particularly around referral and evaluation practices. First, policies like universal age-normed developmental screeners given to all students at kindergarten entry could reduce disparities in the likelihood of special education identification in kindergarten by age. Rather than relying solely on teachers to flag students who they perceive as being behind, universal screeners would provide an initial benchmark for teachers and parents to assess children's developmental progress (McIntyre et al., 2017). In this vein, many states have recently begun mandating the use of kindergarten readiness assessments to identify students who may be at risk of falling behind in literacy, math, and socioemotional development (Diffey, 2018). However, the purpose of these readiness assessments is not screening for special education eligibility and the kindergarten readiness assessments that states are currently rolling out are not age-normed. Adding age-normed cognitive, physical and socioemotional measures to these kindergarten entry assessments would allow states to fit universal developmental screeners into established assessment programs.

Further, some states plan to use these kindergarten readiness assessments to better target the Response to Intervention (RtI) services in early grades that are often used as a precursor to special education identification (Johnson, 2019; Ohio Department of Education, 2020). Separating "readiness" for school from the developmental differences supported through special education is critical to ensuring that all students who can benefit from special education receive those supports. For example, there also been a move towards funding universal screeners for specific learning disabilities. Two states recently passed laws requiring universal screenings for dyslexia (Indiana S.217, 2018; South Carolina H.3414, 2017) to reduce the number of students who are undiagnosed or diagnosed long after first experiencing reading difficulties. Like the kindergarten readiness assessments, these policies have not be systematically evaluated. Further, although these disability specific screeners may reduce gaps in the likelihood of particular diagnoses, the use of universal screeners intended to identify specific learning disabilities like dyslexia are not likely to close the age-related identification gap alone given the diversity of developmental differences supported through special education.

Teacher professional development targeted at general education teachers could also help teachers better distinguish between typical developmental differences between children in early grades and signs of disability. For example, there is evidence that general educators may be more likely to perceive the same achievement and behaviors more negatively than do special educators, so that general educators refer students at higher rates than teachers with specialized training in teaching children with exceptionalities (Podell & Tournaki, 2007). Improved training for teachers in the early elementary grades could reduce the likelihood of disparities in referral rates by age, particularly for general education teachers who may be the first to identify emergent needs and to recommend special education referral. The lack of heterogeneity in effects across school districts also suggests that implementation of universal developmental screeners and changes to teacher professional development around special education referral practices would be impactful for all school districts.

Finally, the finding that the students in kindergarten cohorts with wide age ranges are more likely to be placed in special education than their young peers in cohorts with narrow age ranges reveals an unintended spillover effect of parents delaying their child's school entry. Recently, policymakers in Michigan have considered changes to the compulsory attendance law so that kindergarten enrollment is mandatory at age five, which would reduce the ability of parents to choose to redshirt their children (Chambers, 2019). Further, a number of the developmental kindergarten programs allow children who are eligible to enroll in kindergarten to elect to delay entry in order to participate in a developmental kindergarten year. To reduce the age variability in traditional kindergarten classrooms, policy makers could consider restricting the program to children who are still preschool age.

These findings also have implications for future research. First, the effect of being young for grade on special education identification has often been interpreted as representing an overplacement in special education or a misdiagnosis of ADHD of the youngest students (Dhuey & Lipscomb, 2010; Elder, 2010; Ma et al., 2012). However, these differences in identification rates could actually indicate an underplacement of the oldest students (Dhuey et al., 2019) or an appropriate allocation of special education services to narrow the developmental gaps between students who are a year apart in age (Bedard & Dhuey, 2006; Elder & Lubotsky, 2006; McEwan & Shapiro, 2008). Evidence of whether the higher likelihood of identification for the youngest students represents a misallocation of resources, and if so in which direction, is critical for designing policy solutions to address the age-related imbalance in special education identification rates.

More importantly, the impact of this age related disproportionality on the academic and socio-emotional outcomes of children is understudied. Receiving special education services in early grades can be beneficial for students, particularly those with speech-sound or language delays that predict weaker literacy skills in later elementary school (Bird, Bishop, & Freeman, 1995; Bishop & Adams, 1990; Nathan, Stackhouse, Goulandris, & Snowling, 2004; Peterson, Pennington, Shriberg, & Boada, 2009; Sices, Taylor, Freebairn, Hansen, & Lewis, 2007; Skebo et al., 2013). Therefore, the younger students who are induced into special education for speech or language delays because of their age may benefit from these higher identification rates. Similarly, if older students go undiagnosed because their absolute age premium obscures developmental delays, the lower identification rates for the oldest students may have negative effects on their future academic outcomes (Guaralnick, 1998; Odom et al., 2004). On the other hand, special education identification may have negative impacts on students related to stigma, lowered expectations, and placements in restrictive environments apart from typically developing peers (Dowling, 1985; Kauffman & Badar, 2013; Lalvani, 2015; McLeskey, Landers, Williamson, & Hoppey, 2012; Shifrer, 2013).

The present study is limited in a number of ways. First, the regression discontinuity design estimates the effect of school starting age right at the cutoff, which means that the estimated difference is between the students at the two extremes of the age eligibility range. Thus, these findings may not be generalizable to students who are relatively old or young (i.e., in the bottom or top quartile of age) for their grade but not the youngest or the oldest. Second, although the overall attrition rates in the sample are low, there is some evidence that students who exit from Michigan public schools after kindergarten are more likely to be Black and low-income which suggests differential attrition that could bias the results. For example, if the youngest students are more likely to be placed in special education which increases their likelihood of exiting the public schools, this would bias the follow-up year results toward zero. Finally, the present study does not include measures of special education referral separate from identification. Disentangling whether a greater share of the referrals for the youngest students result in eligibility determinations than those for the oldest students or vice versa will provide valuable insight into which aspects of special education identification favor the youngest students.

Special education programs provide individualized instruction and supports to students with eligible disabilities and can be a powerful tool to improve academic outcomes for children with developmental differences. However, a fundamental challenge is correctly identifying those students who will be best served by being placed in special education programs. Longstanding descriptive evidence of disparities in identification rates by sociodemographic characteristics has raised important questions about the equity in special education placement. I find causal evidence that children who are young for their grade are more likely to be placed in special education and that these effects last through eighth grade. Future work evaluating reforms to the special education referral and evaluation process, and the impact of higher and lower identification rates on students' long-term academic outcomes is needed.

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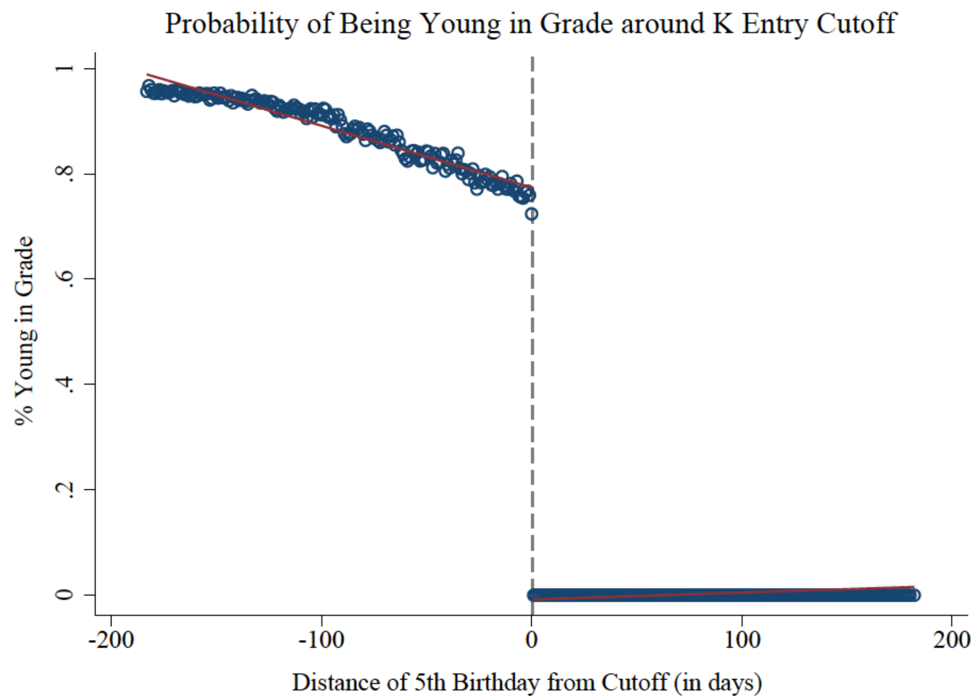
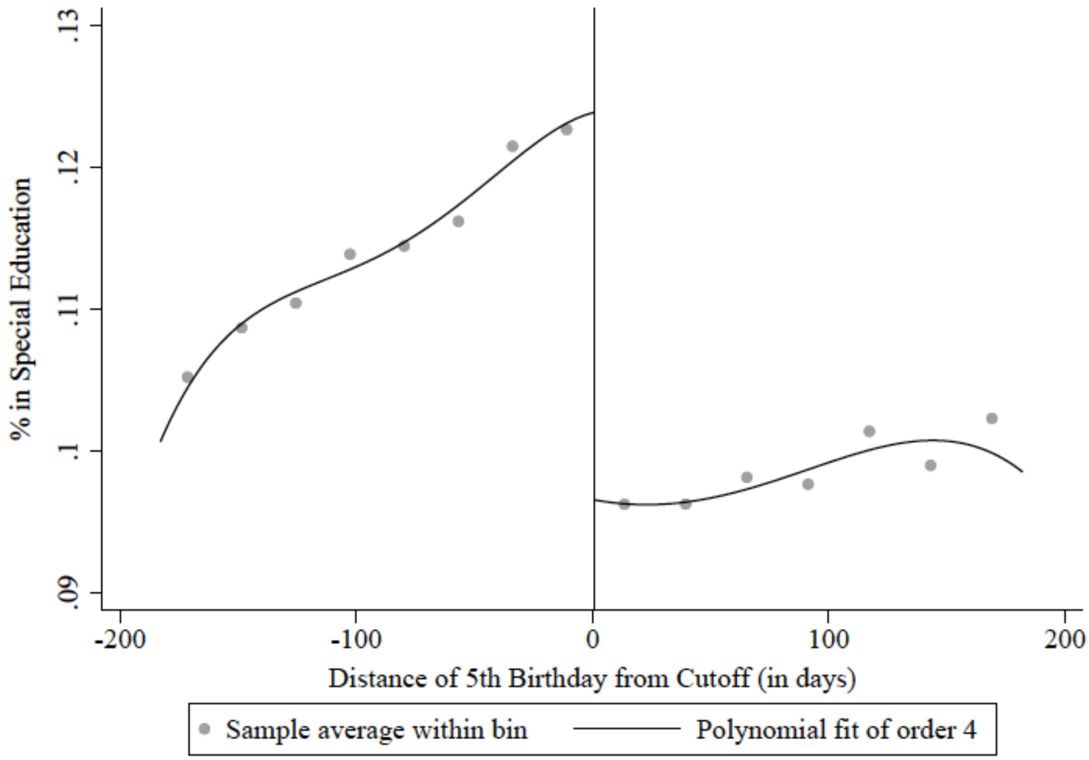
Tables and Figures

Figure 1: Probability of being in the youngest half of the kindergarten age eligibility age range around the kindergarten cutoff



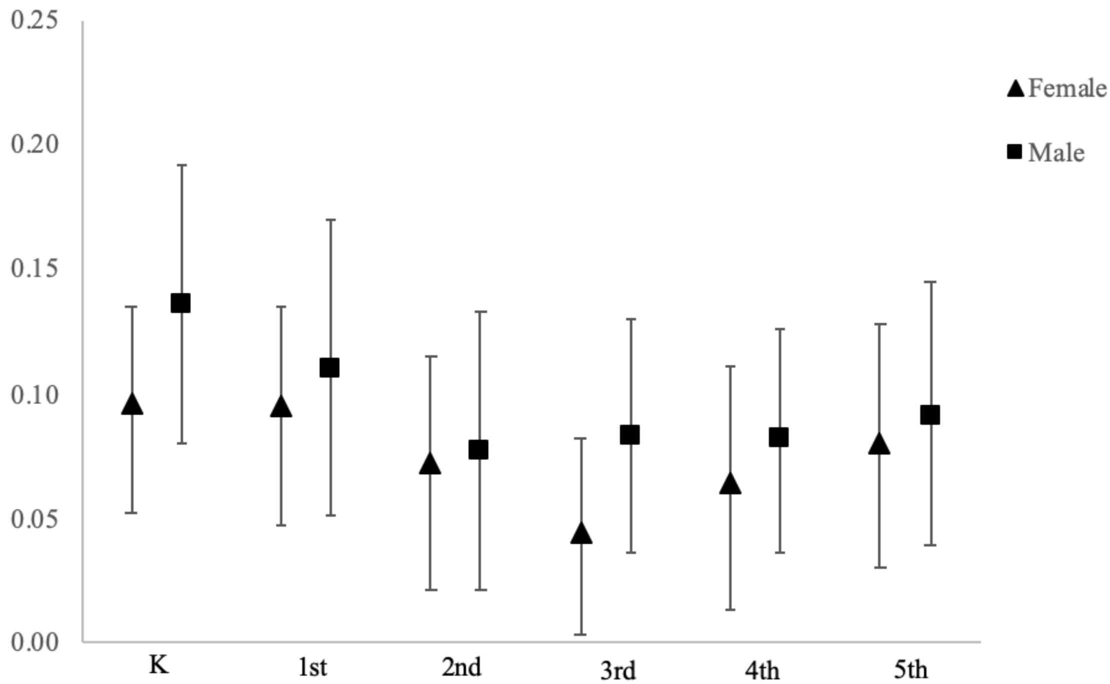
Note: The above figure plots the percent of students born on each day along the running variable who enrolled in kindergarten in the bottom half of the age-eligible distribution on each side of the kindergarten cutoff.

Figure 2. Relationship between a child's birthday and likelihood of receiving special education services in kindergarten.



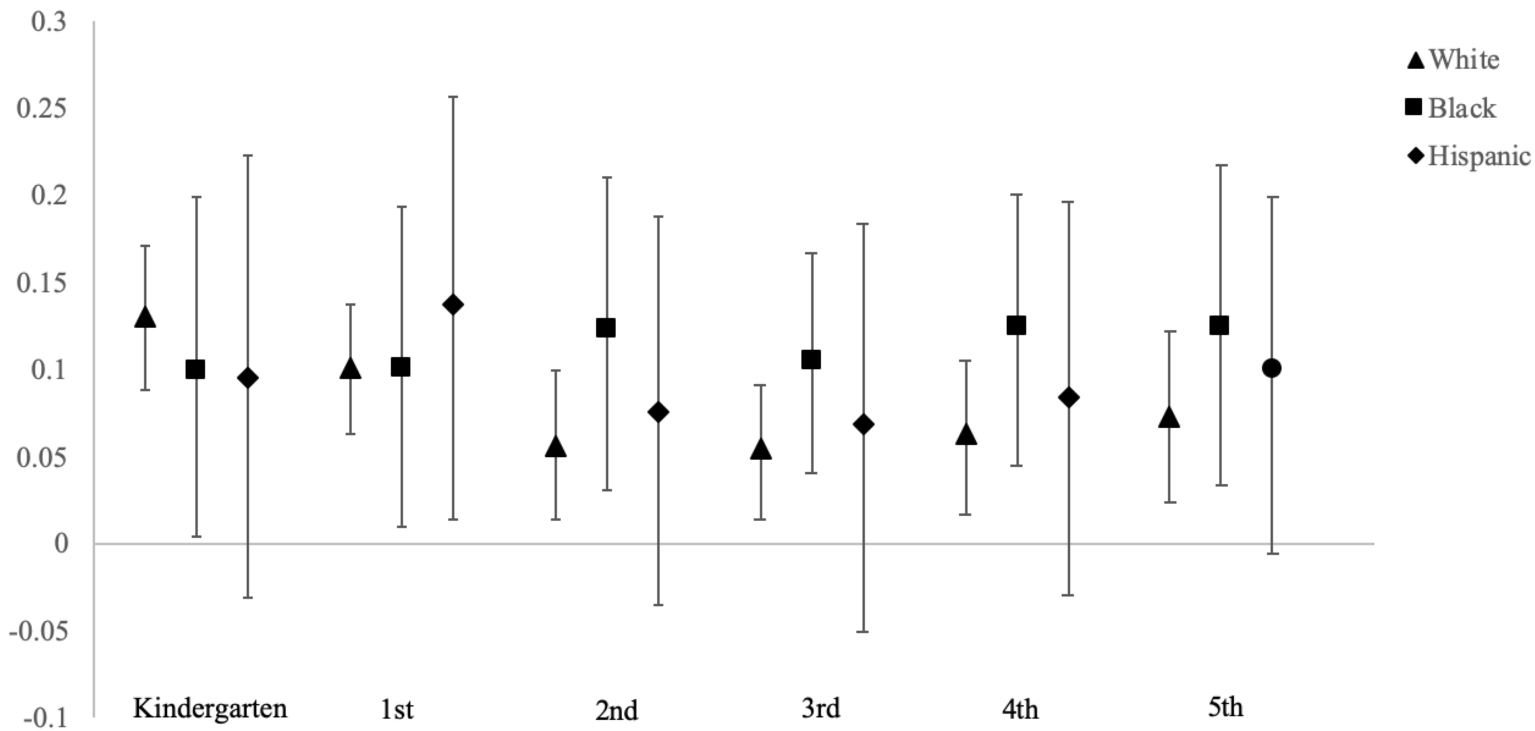
Note: The above figure plots the likelihood of having an IEP in a students' kindergarten eligible year on either side of the cutoff along the running variable for the full sample of students (*N*= 1,285,165). The plot uses integrated mean squared error optimal choice with evenly-spaced bins to mimic the underlying variation in the special education rate along the running variable and a 4th degree global polynomial for visual purpose only. The primary specification for the analyses uses a linear functional form.

Figure 3. Effect of being the youngest in grade on special education identification in kindergarten through fifth grade by gender in standard deviations



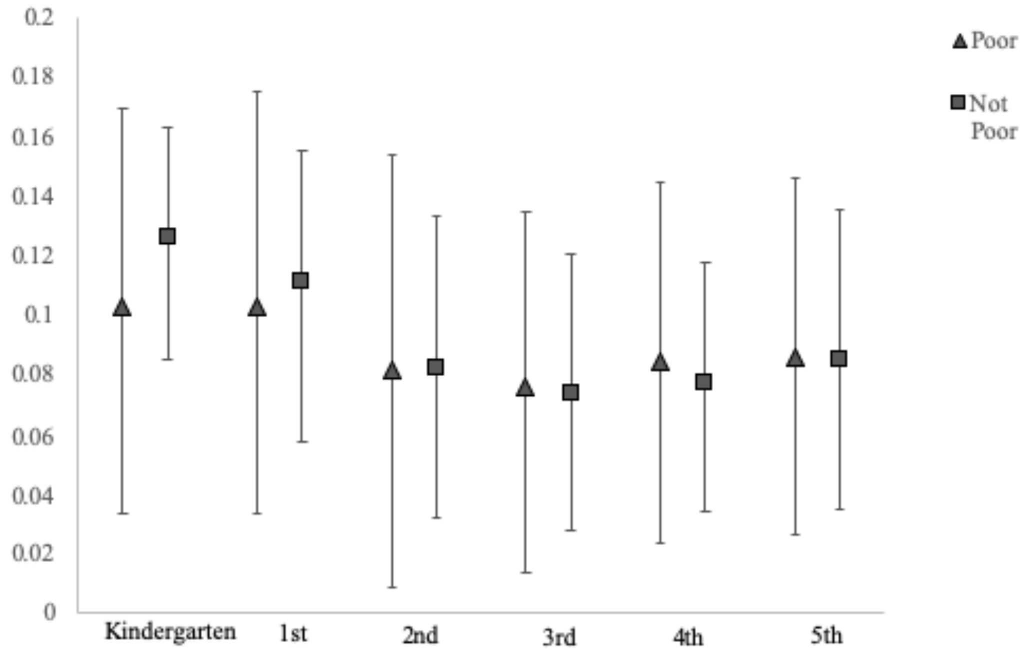
Note: Treatment effects were estimated separately for girls and boys using the primary specification (MSE-optimal bandwidth, polynomial order 1, triangular kernel, covariates, and clustered standard errors at the district-level). Percentage point differences were transformed into effect sizes by dividing the difference and associated confidence interval by the standard deviation of the control group mean within the appropriate MSE-optimal bandwidth.

Figure 4. Effect of being the youngest in grade on special education identification in kindergarten through fifth grade by race and ethnicity



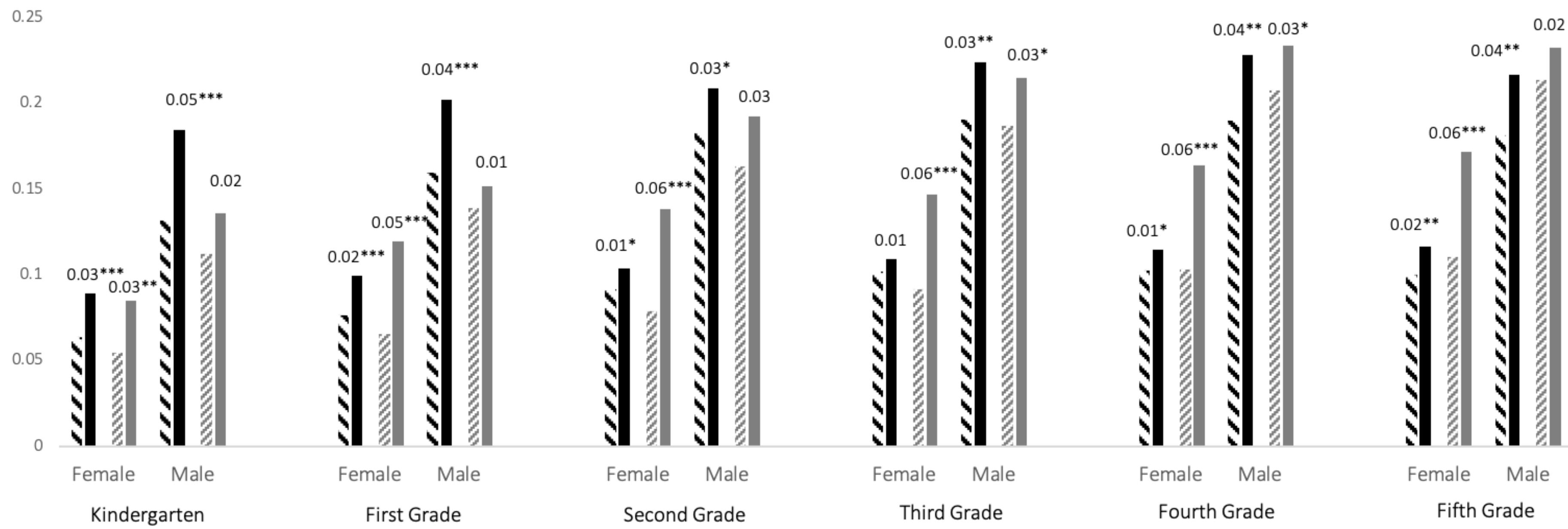
Note: All treatment effects were estimated using the primary specification (MSE-optimal bandwidth, polynomial order 1, triangular kernel, covariates, and clustered standard errors at the district-level). Percentage point differences were transformed into effect sizes by dividing the difference and associated confidence interval by the standard deviation of the control group mean within the appropriate MSE-optimal bandwidth.

Figure 5. Effect of being the youngest in grade on special education identification in kindergarten through fifth grade by free/reduced price lunch receipt



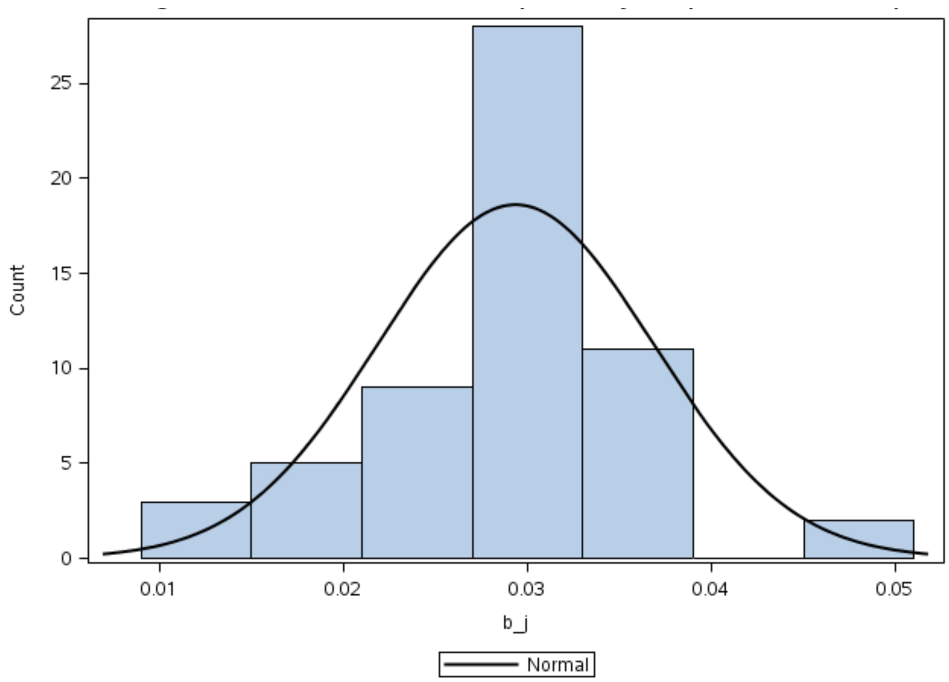
Note: All treatment effects were estimated using the primary specification (MSE-optimal bandwidth, polynomial order 1, triangular kernel, covariates and clustered standard errors at the district-level). Control group means were estimated using observations in the MSE optimal bandwidth for each outcome variable and treatment group means were estimated by adding the control mean and estimated treatment effect.

Figure 6. Effect of being the youngest in grade on special education identification in kindergarten through fifth grade for White and Black student by gender.



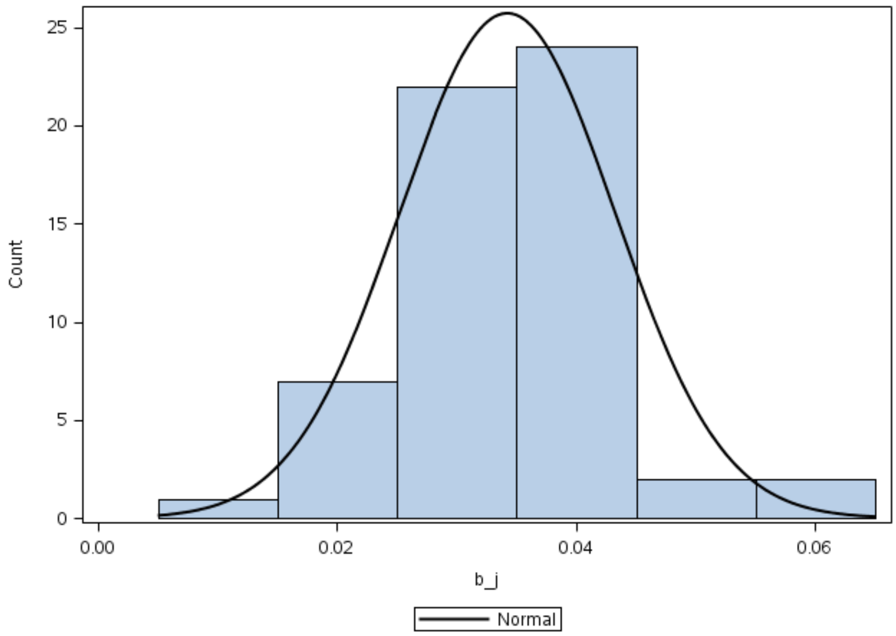
Note: * p<0.05, ** p<0.01, *** p<0.001. ■ White treatment group ▧ White control group ■ Black treatment group ▨ Black control group. All treatment effects were estimated using the primary specification (MSE-optimal bandwidth, polynomial order 1, triangular kernel, covariates and clustered standard errors at the district-level). Control group means were estimated using observations in the MSE optimal bandwidth for each outcome variable and treatment group means were estimated by adding the control mean and estimated treatment effect.

Figure 7. Histogram of ISD-level constrained empirical-Bayes impact estimates on kindergarten special education identification.



Estimated grand mean difference= 0.029, *p*= <0.0001
Estimated tau= <0.0001, *p* on Q-statistic= <0.0372

Figure 8. Histogram of ISD-level constrained empirical-Bayes impact estimates on ever being placed in special education.



Estimated grand mean difference= 0.034, *p*= <0.0001
Estimated tau= <0.0001, *p* on Q-statistic= 0.0113

Table 1. Effect of being eligible to be the youngest in a grade cohort on the likelihood of special education service receipt in kindergarten through 5th grade

	Sped in K	Sped in 1st	Sped in 2nd	Sped in 3rd	Sped in 4th	Sped in 5th
Eligible for K	2.8***	2.6***	1.7***	1.9***	2.1***	2.3***
Robust SE	0.5	0.4	0.4	0.4	0.4	0.4
Robust CI	[1.9, 3.8]	[1.7, 3.6]	[0.9, 2.7]	[1.0, 2.7]	[1.3, 3.0]	[1.5, 3.2]
BW N	93	75	84	83	79	73
Covariates	Y	Y	Y	Y	Y	Y
Cluster Var	District	District	District	District	District	District
Control mean	10.9	12.4	14.0	15.4	16.1	16.1
Effect Size	0.09	0.08	0.05	0.05	0.06	0.06

Note: * p<0.05, ** p<0.01, *** p<0.001. Covariates are female, Black, Hispanic, Asian, FRPL, Migrant, Early On (indicates prior access to early intervention but not receiving services), and fixed effects for eligible year 03-04 and 11-12. The primary specification has a linear functional form and uses a mean squared error optimal bandwidth selector and a triangular kernel. Standard errors are clustered at the district-level (district most enrolled in child's first kindergarten year-i.e., year 0).

Table 2. Effect of enrolling as the youngest in a kindergarten grade cohort on the likelihood of special education service receipt in kindergarten through 5th grade.

	Sped in K	Sped in 1st	Sped in 2nd	Sped in 3rd	Sped in 4th	Sped in 5th
First Stage	0.85***	0.82***	0.82***	0.83***	0.83***	0.80***
First Stage CI	[0.84, 0.86]	[0.81, 0.84]	[0.81, 0.83]	[0.82, 0.85]	[0.82, 0.84]	[0.79, 0.82]
Enroll as youngest in grade	3.3***	3.1***	2.3***	2.3***	2.5***	2.7***
Robust SE	0.6	0.6	0.6	0.6	0.5	0.6
Robust CI	[2.1 , 4.5]	[2.0 , 4.4]	[1.0 , 3.6]	[1.1 , 3.5]	[1.5 , 3.7]	[1.5 , 3.9]
BW N	50	40	39	43	43	37
Control mean	8.8	10.8	12.8	13.9	14.2	14.0
Effect Size	0.12	0.10	0.07	0.07	0.07	0.08

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Covariates are female, Black, Hispanic, Asian, FRPL, Migrant, Early On (indicates prior access to early intervention but not receiving services), and fixed effects for eligible year 03-04 and 11-12. The primary specification has a linear functional form and uses a mean squared error optimal bandwidth selector and a triangular kernel. Standard errors are clustered at the district-level (district most enrolled in child's first kindergarten year- i.e., year 0).

Table 3. Effect of enrolling as the youngest in a kindergarten grade cohort on special education service duration and special education exit in kindergarten through 5th grade.

	Total Years in Special Ed	Percent Years in Sped	Ever in Special Ed	Ever Exited Special Ed	Ever Reentered
First Stage	0.84***	0.84***	0.83***	0.85***	0.87***
	[0.83, 0.85]	[0.83, 0.85]	[0.82, 0.85]	[0.83, 0.86]	[0.85, 0.88]
Enroll	0.22***	2.4***	4.3***	2.2***	0.5***
Robust SE	0.04	0.01	0.7	0.5	0.1
Robust CI	[0.1 , 0.3]	[0.02 , 0.03]	[2.9 , 5.6]	[1.1 , 3.3]	[0.3 , 0.7]
BW N	45	46	43	51	64
Control mean	0.97	12.3	20.3	7.2	0.9
Effect Size	0.10	0.44	0.11	0.09	0.05

Note: * p<0.05, ** p<0.01, *** p<0.001. Covariates are female, Black, Hispanic, Asian, FRPL, Migrant, Early On (indicates prior access to early intervention but not receiving services), and fixed effects for eligible year 03-04 through 11-12. The primary specification has a linear functional form and uses a mean squared error optimal bandwidth selector and a triangular kernel. Standard errors are clustered at the district-level (district most enrolled in child's first kindergarten year- i.e., year 0).

Table 4. Effect of being the youngest in grade on special education identification for students in high and low variance classrooms.

	Identified in Year 0		Ever Special Education	
	High Variance	Low Variance	High Variance	Low Variance
First Stage	0.75***	0.91***	0.72***	0.90***
First Stage CI	[0.71, 0.77]	[0.89, 0.92]	[0.69, 0.75]	[0.88, 0.91]
Enroll - Young	10.69***	0.21	9.12***	1.78
Robust SE	1.46	0.56	1.60	0.93
Robust CI	[7.52, 14.15]	[-0.96 , 1.34]	[5.95, 12.39]	[-0.12 , 3.61]
Bandwidth N	52	60	42	53
Control Mean	12.03	8.19	24.23	18.84
Effect size	0.32	0.01	0.21	0.05

Note: * p<0.05, ** p<0.01, *** p<0.001. Covariates are female, Black, Hispanic, Asian, FRPL, Migrant, Early On (indicates prior access to early intervention but not receiving services), and fixed effects for eligible year 03-04 through 11-12. Standard errors are clustered at the district-level (district most enrolled in child's first kindergarten year- i.e., year 0). P=1, BW= mserd, VCE= NN, Kernel= Tri