Kindergarten to College

Children's Savings Account Program: School Outcomes Report

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Introduction

Children's Savings Accounts

Children's Savings Accounts (CSAs) are interventions that seek to build assets for children to use as long-term investments (Goldberg, 2005; Sherraden, 1991), particularly for postsecondary education. Provided through financial institutions, CSAs generally include progressive features, such as initial seed deposits, financial incentives for attaining certain academic benchmarks, or matches for savings deposits (e.g., Elliott & Lewis, 2014). Distinct among financial aid policies for their cultivation of improved outcomes throughout children's lives, CSAs aim to equip children, particularly those who are disadvantaged, with assets that have demonstrated associations with academic achievement (Elliott, Kite, O'Brien, Lewis, & Palmer, 2016) and educational attainment (Elliott, 2013; Elliott & Beverly, 2011). CSAs also connect households to mainstream financial institutions (Friedline, 2014), activating families to save for their children's futures and their later financial well-being.

Review of Research

Why absences and math/reading scores matter

Children's Savings Account (CSA) programs are long-term investments starting at a child's birth or upon entry into kindergarten. However, their end goal of improving college enrollment and completion does not come to fruition until a child reaches college age. As a result, there is a need for developing clear indicators of interim progress in order to maintain support for CSAs over such a long time period (Elliott & Harrington, 2016).

In a paper written for the Federal Reserve Bank of Boston, Elliott and Harrington (2016) identified interim measures that could serve as a starting point for assessing whether or not CSA programs are on track to deliver their ultimate intended outcomes of college enrollment and completion. These interim measures should be strong predictors of children's enrollment in college and there should be evidence that suggests that CSAs can contribute to the achievement of the interim objective. Elliott and Harrington (2016) state that children's reading and math scores are potential interim CSA metrics but indicate that more research is needed to understand the relationship between receiving a CSA and improving children's reading and math scores. In this study, we examine the relationship between children's math and reading scores. We also examine whether or not CSAs are related to school absences as a potential interim metric. One reason for its inclusion is practical; absences are readily available in administrative data. However, more importantly, research shows that children's absences from school are correlated with their school performance, which is in turn associated with greater educational attainment. We review this research in the next section.

<u>Absences:</u> Research shows that excessive or chronic absences are associated with poorer school outcomes. From kindergarten through high school, students who are frequently absent have lower achievement scores (Applied Survey Research, 2011; Chang & Romero, 2008; Romero & Lee, 2007), even controlling for factors that contribute to both absences and low achievement (Gottfried, 2011).

Specifically, analysis has found gaps in third-grade English assessments and in third-grade math assessments between those with substantial absences in kindergarten/first grades and those with regular attendance (Applied Survey Research, 2011). Students with frequent absences have also been found to be overrepresented among those not graduating from high school (Hickman, Bartholomew, & Mathwig, 2007; Allensworth & Easton, 2005).

Further, students already at risk for school failure may experience greater consequences from the same number of missed days. For example, a review of national data suggests that reading scores for chronically-absent Latino kindergartners were significantly lower than for their peers, even though they had missed similar amounts of school, while, among poor children, chronic absence in kindergarten predicted the lowest levels of educational achievement at the end of fifth grade (Chang & Romero, 2008). Further, while unexcused absences are particularly problematic for student achievement (Gottfried, 2009), aggregate absences may constrain academic progress, regardless of their cause (Ginsburg, Jordan, & Chang, 2014). In addition to its potential independent contributions to school outcomes, attendance may serve as a measure of social and emotional well-being (Rennie Center for Education Research and Policy, 2015), itself a predictor of school success (Durlak, Weissberg, Dymnicki, Taylor, & Schellinger, 2011). Particularly as children age, attendance may be increasingly indicative of social and emotional competencies such as productive use of time, motivation, and initiative (Bronte-Tinkew, Moore, & Shwalb, 2006).

<u>Math and Reading Scores:</u> Math and reading scores, particularly beginning around third grade, are understood as important precursors to later academic achievement (Feister, 2013). Reading proficiency at third grade, in particular, appears highly determinant of academic success across the curriculum. Children who cannot read well in third grade cannot use reading as a tool to engage with school, do their homework, or prepare for exams (Lloyd, 1978). These deficiencies can compromise later educational attainment. For example, in a longitudinal study of nearly 4,000 students, Hernandez (2011) found that those who do not read proficiently by third grade are four times more likely to not graduate from high school than proficient readers; effects are particularly strong for low-income and minority students. Other research indicates that third grade reading is a positive predictor of college attendance (Lesnick, Goerge, Smithgall & Gwynne, 2010). While math skills do not appear as substantial a driver of future academic achievement, triangulating across national data sets, Lee (2012) demonstrates the effects of early math performance on eighth grade math achievement and on college enrollment and completion. Further, as described by Elliott & Harrington (2016), math and reading scores may have multiplier effects on children's academic progress, as they signal a given child's academic potential in ways that may later affect expectations and interactions between teacher and student (Jussim, Eccles & Madon, 1996; Madon, Jussim & Eccles, 1997; Rist, 1977) and potentially lead independently to greater achievement. Given the mutual nature of children's achievement and parents' expectations (Seginer, 1983), children's performance on academic assessments may also encourage or sustain high parental expectations, which in turn support children's further educational attainment (Davis-Kean, 2005; Hossler & Stage, 1992; Pearce, 2006; Peng & Wright, 1994; Vartanian, et al., 2007).

Evidence of asset effects on children's academic outcomes

Since Children's Savings Account programs are relatively new interventions, relatively little research has directly examined the relationship between participation in a CSA and children's academic progress. Early research from Promise Indiana, a CSA intervention begun in Wabash County, reveals some promising results related to the effects of CSAs on children's math and reading scores. In this study, Elliott and colleagues (2016) used regression analysis to separately analyze achievement for the full sample of children and those eligible for free or reduced-price lunch. While the full sample revealed some differences between students without a CSA or not contributing to the account and those saving in Promise Indiana, effects were stronger for the subsample of students eligible for free or reduced-price lunch. For this group, having a CSA had a positive, statistically-significant relationship with both reading and math scores, accounting for nearly 29% of the variance in reading and 23% of the variance in math scores. Considering only those students who have a CSA allowed researchers to further examine the effect of the amount saved on achievement. Here, regression analyses revealed that, for every additional $100 contributed, reading scores increased by 2.08 units and math scores by 2.02 units (Elliott et al., 2016).

Another study, conducted by Elliott (2009), used nationally-representative secondary data to consider the effects of asset-holding on children's educational outcomes. The study used bank savings as a proxy for having a CSA to examine the association that children's savings have with math scores of children ages 12 to 18. Findings indicated that children with savings designated for school have significantly higher math scores than their peers who lack education-designated savings. This study helped establish that savings designated for school may be associated with improved children's math scores.

Further, Elliott, Jung, and Friedline (2010) found that having savings set aside for a child, not specifically for college, is positively associated with higher math scores. However, while such savings are positively related to higher achievement for children regardless of family wealth, the presence of savings for a child had a stronger association with math scores for children living in middle-wealth families than for children from low-wealth families and stronger still for children living in high-wealth families. Subsequently, the same authors examined the effect on math scores of a child having savings designated specifically for college (Elliott et al., 2011). They found that having savings designated for school is associated with higher children's math scores and, further, that the effect does not vary according to family wealth. This finding contributed to the sense that having savings specifically designated for college—as is the case in CSA programs—may better promote improved academic achievement than undesignated savings, particularly because disadvantaged children appear to benefit from savings designated for school as much as high-wealth children do. For a complete review of research on children's savings and their math and reading outcomes, see Elliott and Harrington (2016).

How CSAs may affect academic outcomes

Importantly, CSAs' greatest effects on academic achievement may be indirect—by influencing factors that, in turn, contribute to strong academic achievement—rather than by directly affecting academic achievement itself. There is growing evidence that suggests that CSAs affect several factors also shown in research to affect achievement. In particular, rigorous research from the SEED OK randomized control trial found that CSAs have positive effects on social and emotional development (Huang, Sherraden, Kim, & Clancy, 2014). Specifically, SEED OK research found that receiving a CSA can influence family dynamics in ways that support children's early social and emotional development, including by reducing maternal depression (Huang, Sherraden, & Purnell, 2014) and mitigating the effects of material hardship (Huang, Kim, & Sherraden, 2016) and single-mother household status (Huang, Kim, Sherraden, & Clancy, 2017). These rigorous randomized-control trial findings reveal that CSAs may mitigate as much as 50% of the effects of material deprivation on children's social and emotional development (Huang, Kim, & Sherraden, 2016) and as much as 90% of the difference in social and emotional competency between children in single-mother versus two-parent households (Huang, Kim, Sherraden, & Clancy, 2017). These are particularly significant findings given the importance of social and emotional development for determining how well children perform in a variety of academic contexts and their ability to take advantage of other educational inputs. In a review of extensive data on early absenteeism, Romero and Lee (2007) found that children judged by their teachers to be more socially and emotionally competent attended school more regularly and performed better on achievement tests. To the extent to which CSAs may help to decouple family economic status and measures such as absenteeism, these early children's assets may help to equalize outcomes. Today, poor kindergarteners are four times more likely to be chronically absent than their higher-income peers (Chang & Romero, 2008), and some scholars assert that as much as one quarter of the achievement gap by income can be explained by differences in attendance rates (Goodman, 2014), as absences can have significant effects on math and reading achievement (Ready, 2010; Sanchez, 2012).

In addition to absences, other factors associated with math and reading achievement are affected by the presence of children's assets, particularly through CSAs. These include parental expectations of children's educational attainment, shown to alter engagement and subsequent achievement in school (Hess, Holloway, Dickson, & Price, 1984). SEED OK has established that receiving a CSA can help parents to sustain higher expectations for their children's future educational attainment (Kim, Sherraden, Huang, & Clancy, 2015). More recent SEED OK research by the Center for Social Development focused on CSAs' effects on parental educational expectations as a particular 'pathway' through which asset interventions exert effects on children's outcomes (Kim, Huang, Sherraden, & Clancy, 2017). School readiness indicators, including early math skills, emerging literacy, and attention/self-regulation capabilities, are strongly associated in the literature with academic achievement, including in reading and math (Duncan et al., 2007). On this front, there is a substantial gap in school readiness between those in the highest and lowest socioeconomic statuses (Fernald, Marchman, & Weisleder, 2013), fueled by differences in parenting practices and resources (Halle, 2009; Rodriguez & Tamis-LeMonda, 2011), exposure to stress (National Scientific Council on the Developing Child, 2010; Noble, et al., 2015), and participation in high-quality preschool programs (Duncan & Sojourner, 2012). While CSA research has not yet directly examined effects on school readiness, CSAs' influences on children's early development and on parents' orientation to their children's education suggest potential relationships.

However, reading and math achievement are not entirely predestined when children arrive at school. Students interact with the educational opportunities presented in different ways, some of which may have implications for later achievement. For example, research suggests that children's orientation to learning, including how they rise to new challenges and continually commit themselves to their studies, may help to explain achievement as they progress through school (Bodovski & Youn, 2011). While CSA research has mostly focused on parent expectations rather than children's expectations—in part due to the young age of many children in CSA programs—research demonstrates that children's savings have a slightly stronger relationship with children's expectations than children's expectations have with savings (Elliott, Choi, Destin, & Kim, 2011). Additionally, qualitative research suggests that children's assets encourage the development of college-saver identities in children (Lewis et al, 2016b). These orientations to higher education may encourage engagement with school in ways that facilitate achievement. Further, embedding CSA programs within the school setting may contribute to the development of school cultures and individual competencies associated with these characteristics. This development may be important, given research that shows that gaps in achievement widen with years of school (Farkas, 2003; McNamara, Scissons, & Gutknecth, 2011). To some extent, this may reflect advantaged students' continual climbs, while low-income and otherwise disadvantaged students lose ground, for example, during the summer (Feister, 2013). In other cases, elements of the school environment itself, including poor students' inequitable access to high-quality teaching and concentration in low-performing schools, may help to explain the gaps (Rothwell, 2012).

Program Description

The Kindergarten to College (K2C) Children's Savings Account (CSA) program is a college savings program. The K2C program model opens custodial deposit savings accounts automatically for all students entering kindergarten in a SFUSD school. Disbursement of all initial program deposits and savings matches is restricted to approved postsecondary education purposes. In addition to incentivizing parents to save for their child's college education starting in kindergarten, K2C aims to cultivate a 'college-going' culture among children and families in the public schools and to increase families' financial literacy and inclusion. At the time of this analysis, all K2C CSAs were seeded with an initial $50 investment. Students who qualify for a free or reduced price lunch received an additional $50 initial investment (i.e., $100 total). K2C also matched the first $100 in family contributions to the CSA. In addition, students received a $100 "Save Steady" bonus if their accounts saw at least $10 in deposits per month for 6 months. K2C also piloted additional incentives at select schools, including an attendance incentive, K2C scholarships, and incentives for schools organizing bank field trips.

Previous research finds that as of the 2015-16 school year, 18% of students had at least one contribution to their account (Elliott et al., 2017). For accounts that were four years old, the average total value of accounts that had at least one family contribution was approximately $907 and the average family contribution value was $709 (Elliott et al., 2017). Although families are building educational assets in these CSAs, the dollar amounts are relatively in part due to the short time that they had access to the accounts.

K2C scaled the CSA program across the school district in three phases to cohorts of kindergarten students; kindergarteners in 18 schools received CSAs in 2010–11 (Phase 1), kindergarteners in 18 additional schools received CSAs in 2011–12 (Phase 2), and kindergarteners in the remaining 36 schools received CSAs in 2012–13 (Phase 3). Each of these schools have continued to participate in the K2C program with subsequent kindergarten cohorts. A student's family can withdraw its own contributions up to three times without penalty. Incentive contributions are returned to K2C if the CSA is closed prior to high school graduation or if a student does not attend a postsecondary educational institution by age 25.

Research Question

The analyses in this report address the following research questions:

1. Does receiving a CSA in kindergarten have an impact on students' attendance during the first 4 years of their schooling?
2. Does making a family contribution to the CSA in the first year impact attendance or achievement, measured by third grade math and reading scores, among families who were given a CSA?

Method

Analytic Approach

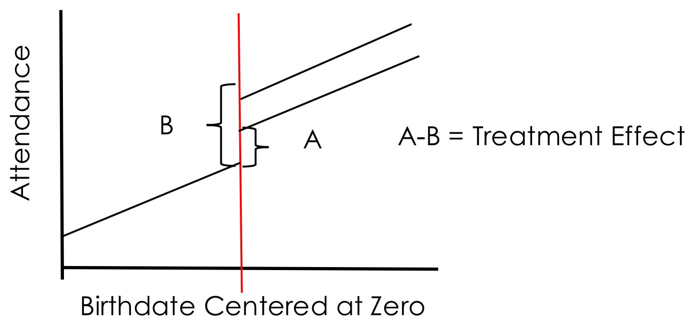
Research question 1. Does receiving a CSA in kindergarten have an impact on students' attendance during the first 4 years of their schooling?

To examine the impact of CSAs on students' attendance, we used a regression discontinuity (RD) approach. RD is the closest quasi-experimental design to a true randomized control trial in that it replaces random assignment with assignment according to an exogenously determined cutoff, which in this case is birthdate. Because receipt of a CSA is based on kindergarten cohort year and kindergarten cohort year is based on birthdate, children who were born before the cutoff for kindergarten entry in the initial K2C implementation year at their school did not receive CSAs (because they entered kindergarten the year before CSAs were provided to kindergarteners in their school). Children born after the cutoff for kindergarten entry in the initial CSA policy implementation year had to wait an additional year to begin kindergarten and, therefore, did receive CSAs. If we assume that no other differences exist between children whose birthdates fall just before rather than just after the cutoff, then any "jump" in later outcomes that happens at the cutoff can be attributed to the effect of the treatment (see Figure 1). In other words, if the cutoff for kindergarten is December 2,[1] then children born on December 1 or before will not receive CSAs, whereas those born on December 2 or after will receive CSAs. With the exception of which kindergarten cohort a child belongs to, there should not be any other systematic differences between children who happen to be born on December 1 compared

[1] Current California law dictates that a student must be 5 years old on or before September 1 to enroll in kindergarten for that respective year. However, in previous cohorts, the cutoff differed across years. Our analytic approach aligns the cutoff dates across cohorts by centering birthdates at 0 to account for these differences.

with December 2. The cutoff itself is arbitrary. However, one limitation of the design is that birthdate is predictive not only of assignment to receive a CSA but also of relative age within grade, which in turn might be associated with attendance. Because of this relationship, it is possible that a "jump" in attendance at the cutoff arises from the fact that children born just after the cutoff are the oldest in their grade, while those born just before are the youngest. To address this limitation, we included children born within 3 months of the kindergarten cutoff the year before the cutoff determined CSA receipt. Including this pre-policy group allows us to assess the "jump" in average attendance at the cutoff that occurred when kindergarten cohort did not determine CSA receipt and then subtract that jump from the jump found when kindergarten cohort did determine receipt of a CSA. Figure 1 presents a stylized graphical presentation of this design. A represents the jump in outcomes for the pre-policy group and B represents the jump for the policy group. Appendix A provides more details about the analytic model.

Figure 1. CSA Treatment Effect Based on Kindergarten Entry Cutoff



Research question 2. Does making a family contribution to the CSA in the first year impact attendance or achievement, measured by third grade math and reading scores, among families who were given a CSA?

To answer research question 2, we used a propensity score weighting approach. We classified students as either being in a family who made a contribution to their CSA when they were in kindergarten (active accounts) or not (passive accounts). Because there are some notable differences between students with active accounts and students with passive accounts (discussed in the next section; Table 1), direct comparisons of attendance and achievement outcomes may not be valid. To improve the comparability of the two groups, we used propensity score weights and covariate regression adjustment (an approach often referred to as doubly robust).

In the analysis, propensity score weights give more weight to students in the passive account group who have similar characteristics as the active account group (based on the measured characteristics listed in Table 1). To estimate average differences in attendance and achievement between the active account and passive account groups, we used weighted regression models that control for the characteristics in Table 1, as well as indicators for which kindergarten cohort a student was in. The regression models also accounted for the clustering of students in schools when calculating standard errors. Appendix B describes the logistic regression model used to estimate each student's probability (or propensity) for being in the active account group based on the measured characteristics and the extent to which the propensity score weights improved comparability between the active account and passive account students.

Table 1. Characteristics of Students with Active and Passive Accounts

Characteristic	Active Accounts (n = 548)		Passive Accounts (n = 3,198)		p Value	Standardized Mean Difference
	Mean	Standard Deviation	Mean	Standard Deviation		
Female	0.504	0.500	0.496	0.500	.749	0.015
Student with disability	0.064	0.245	0.069	0.254	.654	-0.021
English language learner	0.036	0.188	0.033	0.177	.631	0.022
African American/Black	0.038	0.192	0.103	0.304	<.001	-0.213
Hispanic/Latino	0.192	0.394	0.280	0.449	<.001	-0.198
Asian/Pacific Islander	0.500	0.500	0.364	0.481	<.001	0.283
White	0.212	0.409	0.176	0.381	.044	0.094
Other ethnicity	0.058	0.235	0.077	0.267	.128	-0.070
School percentage who met or exceeded math standards	57.544	20.198	50.551	21.403	<.001	0.327
School percentage who met or exceeded ELA standards	57.869	18.474	52.007	19.937	<.001	0.294
School percentage who receive free or reduced-price lunch	57.334	22.303	61.831	23.838	<.001	-0.189

Although the weighting approach improves the comparability of the two groups, the two groups could still differ considerably based on important characteristics we could not measure, such as school engagement, parental involvement, and family income. Therefore, one should interpret the results with this limitation in mind and not infer that group differences in attendance or achievement are due to actively contributing to the CSA.

Setting and Sample

SFUSD is California's seventh-largest school district (72 schools with Grades K–5 or K–8). During the 2015 – 16 school year, most students (56%) received free or reduced-price lunches, one in four (27%) were English language learners, and the district had a majority-minority context (10% African American, 30% Latino, 14% White, 41% Asian/Pacific Islander, 4% multiracial, and less than 1% Native American). The SFUSD high school graduation rate (87%) was slightly higher than the national average (California Department of Education, 2016). SFUSD provides an ideal setting in which to conduct this study because it includes considerable ethnic, cultural, and socioeconomic diversity, and the district is committed to increasing college enrollment rates by helping kindergarten students and their families develop a pathway to college early in their educational trajectories.

To answer research question 1, we compared 4 years of attendance outcomes (kindergarten through third grade for students who progress without being retained) for students with birthdates in the 3 months after the cutoff date for receiving K2C accounts (CSA group) with their counterparts with birthdates in the 3 months before the cutoff date who did not receive the accounts (no-CSA group) during the initial policy implementation year for their schools. We subtracted out any differences in outcomes at the cutoff that occurred in the absence of CSAs.

Primary analyses focus on two groups of students. The first group is the CSA policy group. These students have birthdates 3 months before or 3 months after the cutoff date for kindergarten the first year that kindergarteners would receive a CSA in their school (i.e., the students with birthdates during the 3 months before the cutoff entered kindergarten the year before CSAs were provided, whereas the students with birthdates during the 3 months after the cutoff entered kindergarten the first year that CSAs were provided). The second group is the pre-policy group. These students have birthdates within 3 months of the kindergarten cutoff *1 year before* the cutoff determined receipt of a CSA. For this group of students, the side of the cutoff on which their birthday fell did not determine CSA receipt because neither kindergarten cohort received a CSA. This group is included so that any differences found can be subtracted out from any differences found in the CSA policy group, for example, due to relative age within the grade. Table 2 presents the number of students in each of these groups by kindergarten cohort and phase of implementation.

Table 2. Number of Students by Kindergarten Cohort and Phase of Implementation

Kindergarten Cohort	Phase I		Phase 2		Phase 3		Total
	Pre-Policy Group	CSA Policy Group	Pre-Policy Group	CSA Policy Group	Pre-Policy Group	CSA Policy Group	
2008–09	288						288
2009–10	288	327	308				923
2010–11		248	252	254	674		1,428
2011–12				242	559	744	1,545
2012–13						652	652
Total	576	575	560	496	1,233	1,396	4,836

Table 3 presents descriptive statistics and mean absences the first through fourth years after the first year a student is observed in kindergarten for the entire sample (first column), for students with birthdays before the relevant kindergarten cutoff (second column) and after the relevant kindergarten cutoff (third column).

Table 3. Student Demographic Characteristics and Absences

	All (N = 4,836)	Three Months Before Cutoff (n = 2,503)	Three Months After Cutoff (n = 2,267)
Student Demographics			

Male	.521	.519	.523
Asian/other	.417	.414	.420
Black	.102	.098	.105
Hispanic	.275	.284	.264
White	.177	.172	.184
Special education	.067	.073	.057
English language learner	.060	.074	.043*
Student Absences			
Year 1	8.77	9.09	8.40
N	4,699	2,503	2,196
Year 2	7.06	7.09	7.03
N	4473	2,356	2,117
Year 3	6.20	5.97	6.47
N	4,224	2,224	2,000
Year 4	6.28	5.99	6.61
N	4,068	2,150	1,918

Note. Chi-square tests were run on student demographics to test differences between students before the cutoff and after the cutoff. Because special education and English language learner status are subjectively decided upon and related to age for grade, the differences between students before and after the cutoff are not an indication of bias in the sample.
$^{*}p < .05$. $^{**}p < .01$.

To answer research question 2, we examined attendance and achievement outcomes for students who were in kindergarten in 2010–11, 2011–12, or 2012–13 (N = 3,746). The students were in one of 73 schools within the school district. All of the students had a CSA opened for them when they started kindergarten.

We excluded 251 students who were missing both school attendance data and third-grade test scores. We were able to examine school attendance for 3,746 students (94% of the total sample), but third-grade test score data were only available for 783 students in the 2011–12 cohort (91% of the 2011–12 cohort, 21% of the total sample).

Overall, 548 of the 3,746 (15%) students were in a family who made a contribution to their CSA. Among these students with active accounts, the median amount contributed during the kindergarten year was $138 (25th to 75th percentile range = $100 to $268) and the median amount contributed from kindergarten to third grade was $320 (25th to 75th percentile range = $100 to $890). Among students with passive accounts, 8% had contributions after the kindergarten year, with a median contribution of $100 for these students (25th to 75th percentile range = $10 to $269).

Compared with students with passive accounts, students with active accounts were more likely to be of Asian/Pacific Islander descent (50% vs. 36%) and be in a school with a higher percentage of students who met or exceeded expectations on the mathematics and English language arts (ELA) state tests (58% vs. 51% for mathematics and 58% vs. 52% for ELA). A comparison of student demographics is provided in Table 1. The comparable numbers for the weighted sample are presented in Appendix B.

Data Sources

To answer the research questions, the study team used three sources of data—(a) K2C provided the research team with transaction records for all students in the school district where students receive K2C accounts students with an open CSA as of July 7, 2016; (b) the school district provided student-level administrative records, and (c) the research team collected publicly-available data on school characteristics, which were linked to students' transaction records.

K2C Account Transaction Records

CSA transaction records included all transactions made between the date the account was opened for the student and July 7, 2016 (the date when data were collected by K2C). All transactions were listed as either a contribution or an incentive. A contribution included any deposit in the student's CSA made by a family member or a guardian. An incentive included any additional funds added to the CSA by the K2C program to encourage college savings (e.g., matched funds for contributions up to $100 per year). The records also included the student's school when the CSA was opened and the year the student received his or her CSA.

School District Administrative Records

Student-level administrative data provided by the school district were used to answer both research questions. These data included the number of excused and unexcused absences for the 4 years after a student is observed in one of the five kindergarten cohorts included in this study (representing kindergarten through third grade for students who progress normally through grades) and student characteristics, specifically gender, race/ethnicity, birthdate, special education status, and English language learner status. Grade 3 proficiency in mathematics and ELA are also used to answer research question 2.[2] For research questions 1 and 2, the outcome variables of interest were four dichotomous indicators for whether a student was absent 10 or more days during each of the first 4 school years. We combined excused and unexcused absences because for students in early grades, most absences are excused; further, research has found that having a large number of total absences, whether excused or unexcused, is associated with poorer academic outcomes (Allensworth & Easton, 2007; Balfanz, 2009; Chang & Romero, 2008). Although the literature generally defines chronic absenteeism as being absent 10% of school days or more, or roughly 18 or more days, this definition is more applicable to older students. Instead, we examine a lower threshold of 10 or more days absent (two full school weeks) as our primary outcome.[3] To examine whether our results are sensitive to this definition of attendance, we conducted a set of robustness checks with alternative definitions. We found similar results when the higher threshold was used (see Appendix C).

For research question 2, we examined achievement as an outcome. For this analysis, we examined whether students met or exceeded the third-grade expectations on the Smarter Balanced Assessment

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[2] Proficiency scores were only available for students in the 2011–12 cohort and were not able to be used for research question 1, which required outcomes data from at least three cohorts due to the RD design.

[3] We use the lower threshold because a small percentage of students in our data are chronically absent (approximately 13% of kindergartners and between 6% and 9% of students in their second through fourth years of schooling). Low probability events make for poor outcome variables due to their lack of variation, increased chance of small sample bias, and increased error.

Consortium (SBAC) tests for mathematics and ELA. Student's achievement levels are determined based on their scaled scores (Table 4; Regents of the University of California, 2017). We did not have access to students' scale scores.

Table 4. Scaled Scores by Achievement Level and Test Subject

	Did not meet expectations	Nearly met expectations	Met expectations	Exceeded expectations
Mathematics	<2381	2381 - 2435	2436 - 2500	>2500
English Language Arts	<2367	2367 - 2431	2432 – 2489	>2489

School-Level Data

Publicly available school-level data were used in the logistic regression models that were used to answer research question 2. These data, published by the school district and the state of California, were collected for all 76 schools. School district data included the number of students enrolled in each school, the school's racial/ethnic composition (the percentage of students identified as Hispanic/Latino, White, African American, Asian, American Indian, Filipino, Pacific Islander, or multiracial), the percentage of students who are English language learners, and the percentage of students receiving special education services. School-level data from the California Assessment of Student Performance and Progress included the percentage of students who receive free or reduced-price lunch, the truancy rate, and the percentage of students who met standards in mathematics and ELA (California Department of Education, 2015).

Results

Research question 1. Does receiving a CSA in kindergarten have an impact on students' attendance during the first 4 years of their schooling?

Impact estimates found that receiving a CSA in kindergarten did not have a statistically significant effect on whether children were absent from school 10 or more times during any of the first 4 years of children's schooling. Estimates of the percentage point difference in the probability of being absent 10 or more times between students who just missed the kindergarten cutoff (CSA group), compared with students who just made the kindergarten cutoff (no CSA group), were not statistically significantly different than in the pre-policy period (Table 5). Identification checks performed on the data used for these analyses found no indication of bias (see Appendix D). Graphical representations of findings are presented in Appendix E.

Table 5. Results from Intent-to-Treat Impact Analysis

Year of schooling	Estimate	Standard Error	*p* Value	*N*
First year (kindergarten)	0.0424	0.0267	.117	4,699
Second year	0.0180	0.0323	.579	4,473
Third year	0.0491	0.0282	.186	4,224
Fourth year	0.0412	0.0262	.120	4,068

Note. Robust standard errors, clustered at the school level, are provided. Discontinuity estimates are obtained parametrically using a linear specification and a 3-month bandwidth around the promotion cutoff, including all student demographic controls found in Table 1, and school fixed-effects.

Research question 2. Does making a family contribution to the CSA in the first year impact attendance or achievement, measured by third grade math and reading scores, among families who were given a CSA?

The analysis of attendance indicates that students with active accounts missed fewer days than similar students with passive accounts (Table 6). The average student in the active account group was 40% less likely to average 10 or more absences in a year than the average student in the passive account group (odds ratio = 0.60). For example, 19% of students with active accounts were absent 10 or more days compared to 29% of students with passive accounts. This result is relatively stable across the alternative definitions of attendance.

Table 6. Results from Analysis of Student Attendance from Kindergarten to Third Grade

Outcome	Estimate	Standard Error	*p* Value	Odds Ratio
Absent 10+ days	-0.512	0.105	<.001	0.60
Absent 5+ days	-0.291	0.117	.012	0.75
Absent 18+ days	-1.015	0.241	<.001	0.36
Total absences (log)	-4.647	0.875	<.001	–

The analysis of student achievement, which only focused on students in the 2011–12 cohort, indicates that students with active accounts were more likely to meet or exceed the third-grade expectations than similar students with passive accounts (Table 7). This was particularly true for ELA, where the average student in the active account group was 53% more likely to meet expectations than the average student in the passive account group (odds ratio = 1.53). For example, 65% of students with active accounts met or exceeded third-grade ELA expectations compared to 55% of students with passive accounts. For mathematics, the estimated difference was similar but only marginally significant using an alpha of .05. For example, 69% of students with active accounts met or exceeded third-grade math expectations compared to 62% of students with passive accounts.

Table 7. Results from Analysis of Student Achievement in Third Grade

Outcome	Estimate	Standard Error	*p* Value	Odds Ratio
Met ELA standards	0.424	0.215	.048	1.53
Met math standards	0.342	0.193	.077	1.41

Limitations

For research question 1, the analyses are an intent-to-treat. This means that they compare all students who were given a CSA in the first year of the policy in their schools, whether or not their family contributed, with all students who did not receive a CSA (within 3 months of the kindergarten cutoff). It is possible that a treatment-on-the-treated analysis, in which comparisons can be drawn between students with a contribution and students without a contribution, might show different results. For example, it is possible that there are positive impacts for the group of students whose family made account deposits that we cannot measure.

Additionally, because the RD approach relies on the comparison between students who did or did not receive a CSA because of which kindergarten cohort they were in, we can examine impacts only for the first year of CSA implementation in a school. It is possible that impacts differed in subsequent years.

The analyses for research question 2 did not account for potentially important factors that might explain differences in attendance and achievement (e.g., student engagement in school or parental education level). This limitation means one should be cautious when interpreting the attendance and achievement differences between students who received CSAs and those who did not, or between those with active accounts and those with passive accounts. It is possible, for example, that families who emphasize school engagement are more likely to contribute to the CSA *and* more likely to encourage student attendance and achievement. In this type of situation, attendance and achievement differences between students with active accounts and passive accounts would be due to family involvement and not the act of contributing to the CSA. Another potentially important limitation in this study is that the analysis was not conducted by family income level. Elliott, Kite et al. (2006) find no evidence of a positive significant relationship between CSAs and children's math and reading scores in an aggregate sample elementary age children, but do find evidence in a sample of low-income children (Elliott, Kite et al., 2016). This has been the case when examining other early education outcomes such as children's social emotional development (Huang, Sherraden, Kim, & Clancy, 2014) as well.

Discussion

This study examined the K2C CSA intervention in San Francisco, CA. K2C is a small-dollar savings account ($50 or $100 initial deposit, depending on income level) intervention that provides every child entering kindergarten in the public school system with a CSA. It is an account into which children, families and third parties (such a grandparents or even employers) can make deposits. A long-term goal of K2C is to improve college enrollment and completion. However, the children examined in this study are still in elementary school, years away from enrolling in college. Following Elliott and Harrington's (2016) recommendation for evaluating CSA programs, the study identified interim metrics (school attendance, math scores, and reading scores) for which we have data as a starting point for examining whether this CSA program is on track toward the intended long-term outcomes of college enrollment and completion. We selected these variables in part because of convenience, as we have access to school administrative data for each of these interim metrics. More importantly, two of the three (math and reading scores) were recommended by Elliott and Harrington (2016) as potential interim metrics for CSA programs. As indicated in Elliott and Harrington (2016) and other literature, there is substantial evidence that these metrics are important predictors of children's success in school. Therefore, if a relationship exists between CSAs and any one of these metrics, it might be concluded that K2C is on track at this stage of the program.

In this study, RD was used to examine whether or not CSAs in kindergarten have an impact on students' attendance during the first 4 years of their school. RD was used because it is one of the most rigorous designs outside of a true randomized control trial. RD replaces random assignment with assignment according to an exogenously determined cutoff, which in this case is a child's birthdate, as it corresponds to placement in a given kindergarten cohort. In this study, impact estimates did not indicate a significant effect of CSAs on whether or not children are absent from school 10 more days during any of the first four years of schooling. However, it is important to note that this study was only able to conduct an intent-to-treat analysis, not a treatment-on-the treated analysis. That is, we were only able to examine the impact of being provided an account, not the impact of having contributions made to an account. It is possible that there is a positive impact for the subgroup of students whose families made deposits to their account. Because the pre-CSA group is comparable only to the full CSA group (but not to the subset of students whose families contributed) a we were not able to conduct a treatment-on-the-treated analysis.

However, there is some evidence that making contributions to the K2C CSA may be associated with improved school outcomes. For example, the average student in this study who is part of the active account group (i.e., had a family contribution to the account) is 40% less likely to have 10 or more absences in a year than the average student who did not have a family contribution to their account. Similarly, findings suggest that children who have active accounts are 53% more likely to meet expectations on standardized third-grade English Language Arts (ELA) scores. These outcomes may indicate that, by providing a vehicle and incentives to encourage families' savings, K2C may help to put children on a path of school achievement that is associated with later educational attainment. For example, research indicates that third grade reading is a positive predictor of college attendance (Lesnick, Goerge, Smithgall & Gwynne, 2010).

[4] Third grade is used here; however, the intent is to use the first state assessment given for reading and math, whether third or fourth grade, depending upon the state.

Although weaker (significant using an alpha of .10), there is also evidence that suggests a correlation may exist between being in the group with active K2C accounts and meeting math expectations. Again, this may serve as a signal that K2C is encouraging achievement consistent with later educational attainment. Triangulating across national data sets, Lee (2012) demonstrates the effects of early math performance on eighth grade math achievement and on the likelihood of entering and completing two- and four-year colleges. While more research is needed, these findings show the potential of CSA programs to have a positive effect on children's reading and math achievement even if relatively modest.

Conclusion

Findings from this study and past studies (e.g., Elliott, Kite et al., 2016) suggest that a CSA alone may not catalyze improvements in attendance, math, and reading; it may take some engagement with the accounts. But, while these findings are promising, they are not definitive and more research is needed. This is perhaps particularly notable given the relatively small K2C account balances at this stage (average total value of accounts that have had at least one family contribution is approximately $907 by the fourth year; average contribution value of $709; Elliott et al., 2017).

However, it is important to point out that the full accounting of whether CSAs can be said to influence children's college outcomes is unlikely to hinge on any single interim metric alone. CSAs have been shown to be predictors of other factors that are known to be important for predicting whether children attend and complete college such as children's socio-emotional development (Huang et al., 2014) and parent's educational expectations for their child (Kim, Sherraden, Huang, & Clancy, 2015). Moreover, there are most likely unidentified interim metrics for researchers to discover that will also help explain the full effects of CSAs on children's college outcomes. Finally, we should not conclude that because a particular CSA program does not seem to have an effect on a specific metric, that another CSA program could not have such an effect if it were designed and/or implemented differently.

Future research might want to examine the effects of K2C on older kids. Researcher suggests that later school achievement might be more strongly influenced by the effects of children's educational asset building. For example, Votruba-Drzal (2006) suggests that these observed effects of parental financial investments on cognitive development might reflect a time lag; it might take a longer time for middle childhood effects to occur (i.e., investments at ages 5 to 6 showing up as early as ages 11 to 12). Other research suggests these effects might not show up until as late as adulthood (Duncan, Brooks-Gunn, & Smith, 1998; Pungello, Kupersmidt, Burchinal, & Patterson, 1996). Additionally, research might examine student's scale scores. For this study we used whether students exceeded the third-grade expectations for math and reading because it was the only data available to us. Researchers also may want to examine whether differences exist by income level. As stated earlier, previous research suggests that findings may be stronger for lower income kids (e.g., Elliott, Kite et al., 2016).

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Appendix A. Research Question 1 Analytic Approach

To examine whether receiving a CSA in kindergarten has an impact on students' attendance during the first 4 years of their schooling, we use an RD design. We present both graphical and reduced form (intent-to-treat) estimates of the impact of receiving a CSA in kindergarten on attendance. Receipt of a CSA is based on birthdate. Students born before the cutoff for kindergarten entry in the initial CSA policy implementation year at their school did not receive a CSA, and students born after the cutoff received a CSA. As is the case in many true randomized experiments, some proportion of students will not follow the district cutoff policy and therefore either will receive a CSA when they should not or not will receive a CSA when they should. Because we cannot determine whether each particular student actually received a CSA, we cannot estimate a treatment-on-the treated estimate of receiving a CSA. However, in the data provided, fewer than 6% of students first appear in a kindergarten cohort that does not correspond with the one to which they should have been assigned according to their birthdate, so we are not concerned that this crossover of treatment dilutes true effects to a large extent.

One limitation of our design is that birthdate is predictive not only of assignment to receive a CSA but also of relative age within grade, which may in turn be associated with attendance. Because of this relationship, it is possible that a jump in attendance at the cutoff arises from the fact that children born just after the cutoff are the oldest in their grade, whereas those born just before are the youngest. To address this limitation, we will include children born within 3 months of the kindergarten cutoff the year before the cutoff determined CSA receipt. Including this pre-policy group allows us to assess the jump in average attendance at the cutoff that occurred when kindergarten cohort did not determine CSA receipt and then subtract that jump from the jump found when the kindergarten cohort did determine receipt of a CSA. Our reduced form model examining the impact on attendance is as follows:

(1) $\text{Attendance}_{ij} = \beta_0 + \beta_1 \text{ Treatment}_{ij} + \beta_2 \text{ Date}_{ij} + \beta_3 \text{ Treatment}_{ij}\text{*Date}_{ij} + \beta_4 \text{ Policy}_{ij} + \beta_5 \text{ Treatment}_{ij}\text{*Policy}_{ij} + X_{ij} + \text{School}_j + e_{ij}$

where Attendance_{ij} is whether student *i* in school *j* has been absent from school 10 or more days during the year; Treatment_{ij} is a dichotomous variable for being born after the cutoff (vs. before); Date_{ij} is the actual birthdate centered such that cutoff date is 0 for student *i* in school *j*; $\text{Treatment*Date}_{ij}$ allows for different slopes on either side of the cutoff for kindergarten enrollment; Policy_{ij} is a binary indicator for being a student from whom the cutoff determines kindergarten entry and receipt of CSAs (compared with prior cohorts for whom the cutoff determined kindergarten entry only); and $\text{Treatment*Policy}_{ij}$ is an interaction between assignment to receive a CSA and the year in which the cutoff determines both kindergarten entry and receipt of CSA. Thus, the effect size is therefore β_5, reflecting a difference-in-differences approach by estimating the effect of assignment to receive a CSA based on the kindergarten enrollment cutoff (i.e., the jump in student outcomes associated with receipt of a CSA), above and beyond the effect of the cutoff in a nonpolicy implementation year on student attendance (i.e., any jump in student attendance associated with being the oldest vs. youngest within a grade). X_i represents a vector of demographic characteristics for student *i* in school *j*, which is included for precision, and School represents school fixed effects. The model accounts for whether students were in implementation Phases I through III by modeling school fixed effects (which are perfectly correlated with phase of implementation given that no school is included in multiple phases). Robust standard errors are used to account for clustering of students within schools.

Several strategies can be used to specify the underlying functional form when relying on an RD design, the first is to estimate the equation non-parametrically using kernel-weighted local polynomial smoothing as proposed by Hahn, Todd, and van der Klaauw (2001) and later developed by Porter (2003) to include higher-order polynomial estimators. Nonparametric strategies reduce the possibility of misspecification bias inherent in parametric models. However, when the selection variable is discrete, as in this case, a nonparametric estimator may lead to more biased estimates because it is not possible to compare averages within an arbitrarily small neighborhood around the cutoff (Lee & Card, 2008). We therefore follow Lee and Card (2008) and estimate parametrically using a linear specification, allowing for differences in slope on either side of the discontinuity, and limiting the analysis to students within 3 months of the cutoff. We present graphical evidence that this specification appears to fit the data well and check the robustness of our findings using different bandwidths (1, 3, and 6 months) and polynomial orders (1, 2, and 3).

Appendix B. Research Question 2 Analytic Approach

We used a logistic regression model to estimate each student's probability (or propensity) for being in the active account group based on the measured characteristics. We ran a separate logistic model for each kindergarten cohort. For each student in the passive account group, we converted the student's propensity score into a weight that represents the odds of the student being in the active account group. Passive account students with characteristics more similar to the active account students get more weight in the analysis than passive account students with characteristics less similar to the active account students. Students in the active account group all received a weight of 1.

Compared with the unweighted characteristics in Table 1, Table B1 shows that the standardized mean differences for all the characteristics are very close to zero when the weights are applied, and no differences are statistically significant.

Table B1. Characteristics of Students With Active and Passive Accounts With Propensity Score Weights Applied

Characteristic	Active Accounts (n = 548)		Passive Accounts (Weighted) (n = 3,198)		p Value	SMD
	Mean	Standard Deviation	Mean	Standard Deviation		
Female	0.504	0.500	0.501	0.500	.921	0.005
Student with disability	0.064	0.245	0.066	0.248	.868	-0.008
English language learner	0.036	0.188	0.035	0.184	.858	0.009
African American/Black	0.038	0.192	0.038	0.191	.973	0.002
Hispanic/Latino	0.192	0.394	0.191	0.393	.972	0.002
Asian/Pacific Islander	0.500	0.500	0.501	0.500	.962	-0.002
White	0.212	0.409	0.213	0.409	.955	-0.003
Other ethnicity	0.058	0.235	0.057	0.232	.903	0.006
School percentage who met or exceeded math standards	57.544	20.198	57.565	19.699	.982	-0.001
School percentage who met or exceeded ELA standards	57.869	18.474	57.879	18.362	.990	-0.001
School percentage who receive free or reduced-price lunch	57.334	22.303	57.251	23.172	.937	0.004

SMD = standardized mean difference (i.e., the difference between the mean for the active accounts group and the mean for the passive accounts group, divided by the standard deviation for the passive accounts group).

Appendix C. Robustness Checks

Our main model for research question 1 impact estimates uses 10 or more absences in a year as the outcome variable and includes student level demographic covariates to increase precision and school fixed effects in order to compare students within schools and therefore take into account any effect of school or implementation phase. Estimates are stable regardless of the inclusion of covariates or fixed effects (Table C1).

Table C1. Effect of Receiving a CSA on Probability of Being Absent 10 or More Times: Adding Covariates and Fixed Effects

Year				*N*
First year (kindergarten)	0.0524 (0.0306)	0.0391 (0.0275)	0.0424 (0.0267)	4,699
Second year	0.0158 (0.0322)	0.0061 (0.0322)	0.0180 (0.0323)	4,473
Third year	0.0536 (0.0293)	0.0488 (0.0287)	0.0491 (0.0282)	4,224
Fourth year	0.0383 (0.0270)	0.0322 (0.0263)	0.0412 (0.0262)	4,068
Student-level covariates		X	X	
School fixed effects			X	

Note. Robust standard errors, clustered at the school level, are given in parentheses. Discontinuity estimates are obtained parametrically using a linear specification and a 3-month bandwidth around the promotion cutoff, including all student demographic controls found in Table 3, and school fixed effects.
The following indicate significance: (*$p < .05$. **$p < .01$).

The percentage of students absent 10 or more times and the proportion of students chronically absent is not statistically significant for any year, although log transformed absences is statistically significantly greater in the first and third year for students who received a CSA (Table C2).

Table C2. Effect of Receiving a CSA on Attendance Outcomes

Year	Log Absences	Absent 10+ Times	Chronically Absent (10% or more)	*N*
First year (kindergarten)	0.149* (0.0622)	0.0424 (0.0267)	0.0252 (0.0206)	4,699
Second year	0.0168 (0.0723)	0.0180 (0.0323)	0.0177 (0.0175)	4,473
Third year	0.207** (0.0591)	0.0491 (0.0282)	0.0269 (0.0177)	4,224
Fourth year	0.0177 (0.0659)	0.0412 (0.0262)	0.0229 (0.0196)	4,068

Note. Robust standard errors, clustered at the school level, are given in parentheses. Discontinuity estimates are obtained parametrically using a linear specification and a 3-month bandwidth around the promotion cutoff, including all student demographic controls found in Table 3, and school fixed-effects.
*$p < .05$. **$p < .01$.

To check the robustness of our findings to model specification, Table C3 presents the results of the impact of being in a kindergarten cohort provided CSAs on the likelihood of being absent 10 or more times in a year using various bandwidths and polynomial orders. The results in this table are obtained using the model including all student demographic controls and school fixed effects with linear, quadratic, and cubic polynomial specifications and bandwidths of 6 months, 3 months, and 1 month. For the 6-month bandwidth, there are statistically significantly negative effects (an increase in the likelihood of being absent 10 or more times) for the third year of schooling. For the 1-month bandwidth, there are statistically significantly negative effects for the first year of schooling. Given the number of regressions, however, we would expect to see one or two iterations be statistically significant due to random chance, and the lack of consistency in these results suggest caution should be used when considering these results.

Table C3. Effect of Receiving a CSA on Probability of Being Absent 10 or More Times by Functional Form and Bandwidth

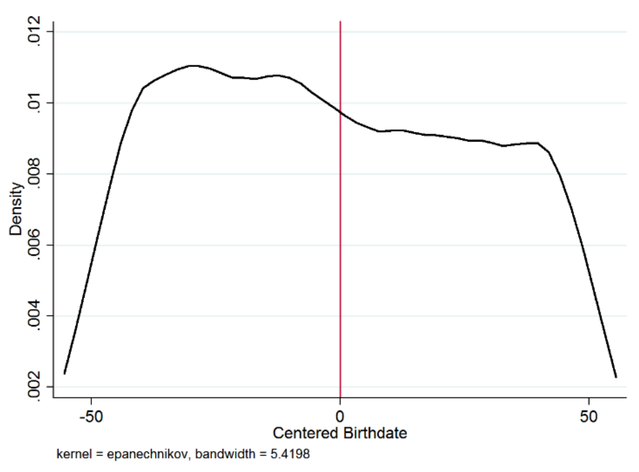
Year	Linear	Quadratic	Cubic	*N*
	Six Months			
First year (kindergarten)	0.0362 (0.0213)	0.0357 (0.0210)	0.0357 (0.0210)	9,147
Second year	0.0047 (0.0218)	0.0041 (0.0219)	0.0044 (0.0219)	8,704
Third year	0.0479* (0.0202)	0.0488* (0.0201)	0.0483* (0.0202)	8,215
Fourth year	0.0056 (0.0170)	0.0052 (0.0169)	0.0062 (0.0169)	7,887
	Three Months			
First year (kindergarten)	0.0424 (.0267)	0.0421 (0.0267)	0.0421 (0.0266)	4,699
Second year	0.0180 (0.0323)	0.0186 (0.0323)	0.0188 (0.0322)	4,473
Third year	0.0491 (0.0282)	0.0487 (0.0281)	0.0492 (0.0280)	4,224
Fourth year	0.0412 (0.0262)	0.0414 (0.0261)	0.0418 (0.0262)	4,068
	One Month			
First year (kindergarten)	0.118* (0.0503)	0.117* (0.0498)	0.116* (0.0499)	1,569
Second year	-0.0071 (0.0439)	-0.0074 (0.0441)	-0.0077 (0.0441)	1,496
Third year	0.0595 (0.0477)	0.0595 (0.0476)	0.0594 (0.0475)	1,398
Fourth year	0.0838 (0.0487)	0.0845 (0.0489)	0.0842 (0.0489)	1,352

Note. Robust standard errors, clustered at the school level, are given in parentheses. Discontinuity estimates are obtained parametrically using the given polynomial degrees and bandwidths around the promotion cutoff, including all student demographic controls found in Table 3, and school fixed effects.
*$p < .05$.

Appendix D. Identification Checks

A chief concern in any RD analysis (the design used to answer research question 1) is the possibility of manipulation of the assignment variable around the cutoff (Urquiola & Verhoogen, 2009). In this context, for example, we would be concerned if it appeared that parents were choosing to have their children born on the first date after the kindergarten cutoff rather than the day before or vice versa in an attempt to determine which kindergarten cohort their children were in. Under this scenario, one would expect to see a discontinuity in the birthdate distribution around the cutoff date, or "lumping" of birthdates either right after or right before the cutoff. Because the formal test developed by McCrary (2008) is not appropriate in this case as it relies on local linear regression, which can lead to incorrect inferences when the assignment variable is discrete (Lee & Card, 2008), we present graphical evidence to dispel any concerns. Figure D1 shows that the overall distribution of birthdays is smooth around the cutoff.

Figure D1. Density of Birthdate



The use of RD also relies on the assumption that there are no discontinuities in other student characteristics associated with outcomes at the cutoff. Figures D2 through D4 address this concern by plotting the mean value of observable student demographic characteristics against attendance close to the cutoff. The figure shows that there are no discontinuities in observed student characteristics at the cutoff.[4]

[4] Because special education classification and English language learner classification are dependent on age for grade, they are not appropriate observables to plot across the centered birthdate threshold. Only nonmalleable observables are used as a check.

Figure D2. Percentage of Asian/Other Students by Centered Birthdate

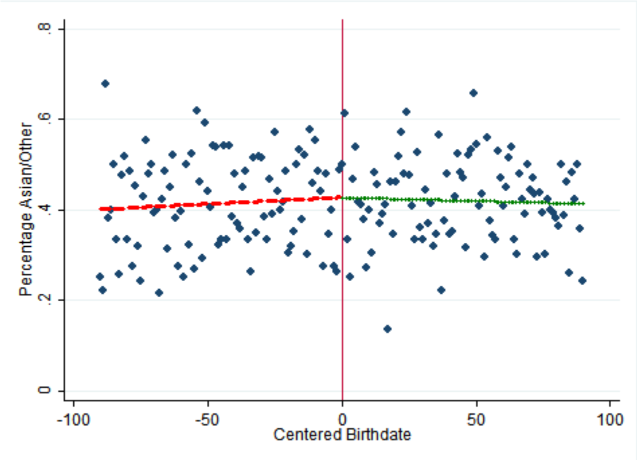


Figure D3. Percentage of Hispanic Students by Centered Birthdate

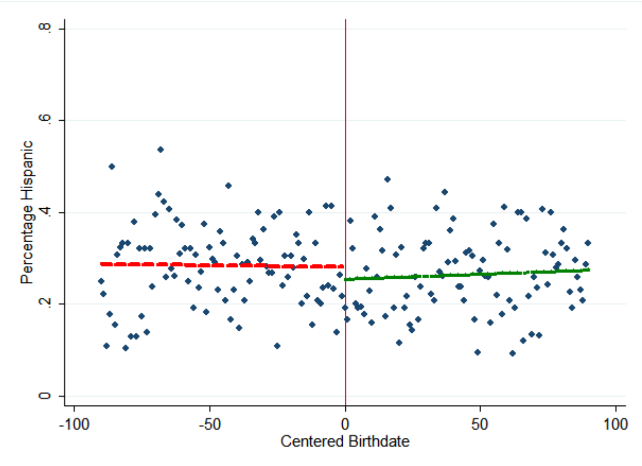
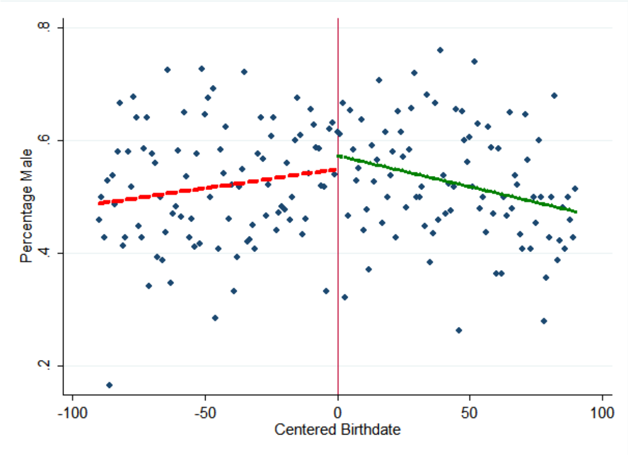


Figure D4. Percentage of Male Students by Centered Birthdate



Appendix E. Graphical Findings

Figures E1a and E1b through E4a and E4b present the scatterplot and local linear smoothing (with 95% confidence intervals) of the probability of being absent 10 or more times, calculated separately for each side of the cutoff[5] for the policy and pre-policy groups 1–4 years after entering kindergarten (kindergarten through third grade for students who progressed normally without retention). The linearity of the relationship between birthdate and likelihood of being absent 10 or more times in a year make us confident that a linear specification is appropriate over this bandwidth for the impact analyses, although we test higher-order polynomials and various bandwidths as well.

Figure E1a. Fraction of Students With 10 or More Kindergarten Absences by Birthdate: CSA Policy Group

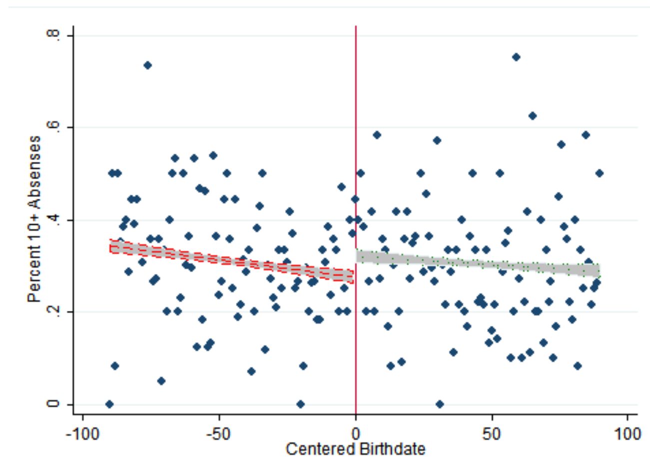
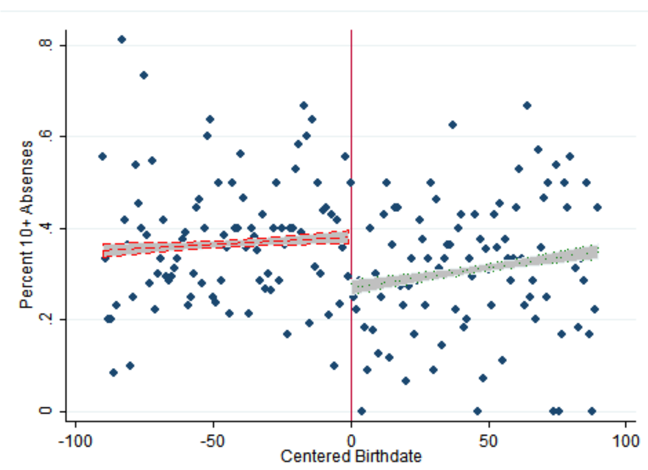


Figure E-1b. Fraction of Students With 10 or More Kindergarten Absences by Birthdate: Pre-policy Group



[5] Triangle kernel was used.

Figure E2a. Fraction of Students With 10 or More Second-Year Absences by Birthdate: CSA Policy Group

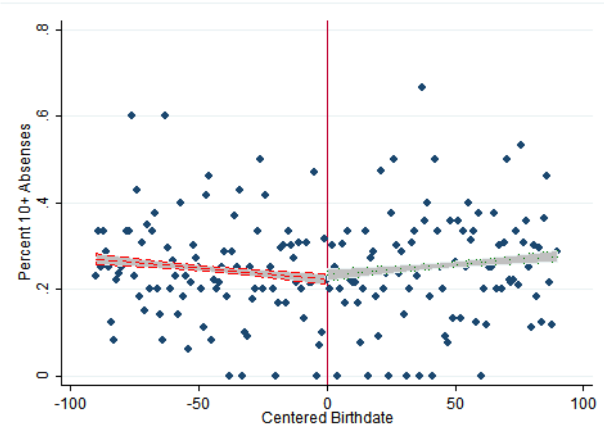


Figure E2b. Fraction of Students With 10 or More Second-Year Absences by Birthdate: Pre-policy Group

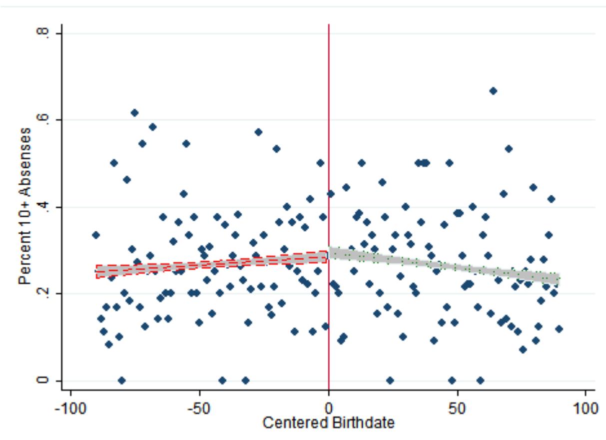


Figure E3a. Fraction of Students With 10 or More Third-Year Absences by Birthdate: CSA Policy Group

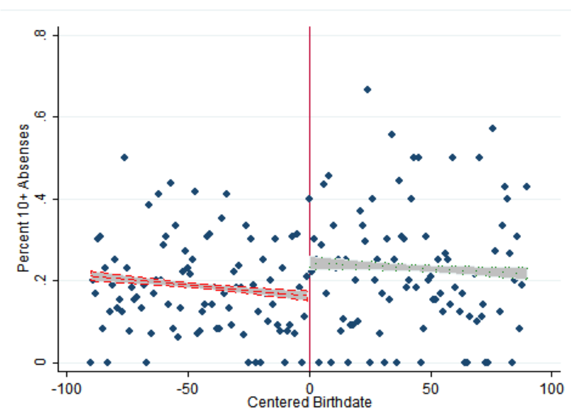


Figure E3b. Fraction of Students With 10 or More Third-Year Absences by Birthdate: Pre-policy Group

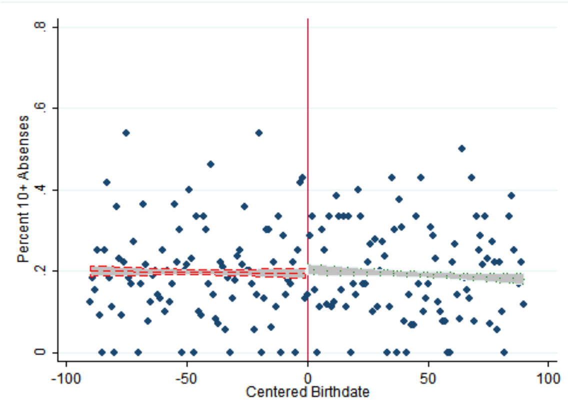


Figure E4a. Fraction of Students With 10 or More Fourth Year Absences by Birthdate: CSA Policy Group

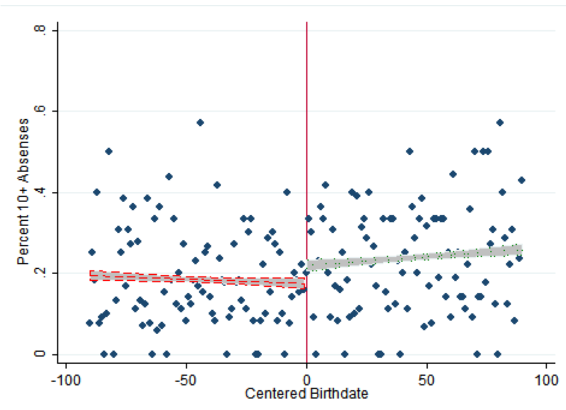
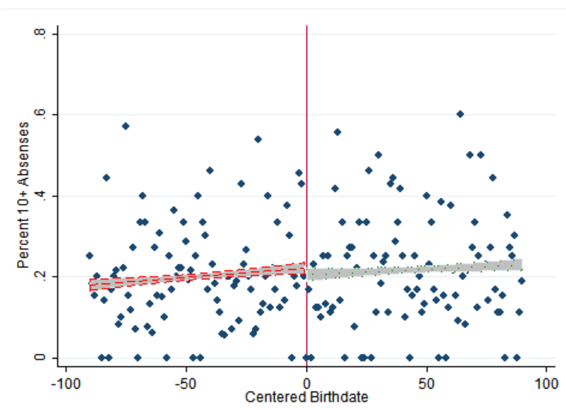


Figure E4b. Fraction of Students With 10 or More Fourth Year Absences by Birthdate: Pre-policy Group



Visually, it appears that there was a slight increase in the likelihood of being absent 10 or more days associated with receiving a CSA in kindergarten (Figure E1a), whereas in the prior year students with birthdays just after the cutoff were actually less likely to be absent 10 or more days (Figure E1b). In the third and fourth years, there appeared to be a slight increase in the likelihood of being absent 10 or more days associated with being in the cohort to receive a CSA in kindergarten and no difference in likelihood for students with birthdays just after the cutoff in the prior year (Figures E3a, E4a, E3b, and E4b). However, these differences are not significant.

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