Combining children's savings account programs with scholarship programs: Effects on math and reading scores

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ABSTRACT

The study examines school data and their association with participation in the Wabash County Promise Scholarships program, which combines Children's Savings Accounts (CSAs) with scholarships. CSAs are interventions designed to build educational assets for school age children. Policy makers are increasingly turning to CSAs as a way to augment efforts for improving children's educational outcomes. Findings from this study provide some evidence that having a CSA combined with a scholarship is associated with higher math and reading scores. Findings are strongest among the subsample receiving free/reduced lunch. Further, findings suggest that being a saver (i.e., having at least one family or champion contribution) in Promise Scholars is associated with higher math scores but not reading scores. Finally, evidence suggests that CSAs combined with scholarships in the Promise Scholars program are more closely associated with children's math and reading scores than only CSAs.

1. Introduction

Racial, ethnic, and socioeconomic disparities in college enrolment and college completion remain prevalent in the United States (Perna & Kurban, 2013). A higher proportion of Asians and Whites are attaining four-year degrees compared to minority students and this outcome is more likely to be observed for students from high socio-economic backgrounds (Jones, 2013). Some scholars argue that these continued disparities are attributed to persistent, systemic barriers that contribute to cumulative differences in access to key educational resources that affect student learning and academic achievement in K-12 schools (Carter, Welner, & Ladson-Billings, 2013). Other scholars posit that higher education has become an engine exacerbating inequality through the merit-based college admission system, its commitment to equally supporting race-based and socioeconomic-based affirmative action policies and programs has been fading dramatically reflected by rising college tuition and the growing proportions of students from upper-middle and upper-class families enrolled at selective colleges and universities (Espenshade, 2012; Kahlenberg, 2012; Wilson, 2012). Federal educational policies and interventions such as the Higher Education Act (HEA) and Race to the Top are put in place to address education inequity and inequality by providing academic and social support that supplements what children and families are unable to access in the education pipeline (Ellis, 2015). These policies provide students opportunities to engage in interventions intended to enhance their academic preparation for college (Allen & Griffin, 2006; Cabrera et al., 2006; Gandara, 2001; Hagedorn & Prather, 2006; Savitz-Romer & Bouffard, 2012; Tierney, 2002; Ward, 2006).

The rising college costs are a significant barrier to college enrollment and completion (DesJardins, Ahlburg, & McCall, 2002; Paulsen & John, 2002; St. John, Paulsen, & Carter, 2005). The role of financial aid in alleviating college costs is well understood in the literature. Research suggests that the type of financial aid package a student receives (e.g., federal Pell grants, loans, work study, merit-based scholarships) influences the types (four-year vs two-year institutions; institution selectivity) of colleges and universities students decide to enroll in (Hossler & Gallagher, 1987; Long, 2004; Perna & Titus, 2004), student enrollment, disenrollment, and reenrollment in college (DesJardins & McCall, 2010). It also influences students' commitment to institutions, integration into the campus community, and academic achievement in college (St. John, Paulsen, & Starkey, 1996).

1.1. Scholarships and children's savings accounts

Traditional scholarship programs are designed to increase college attainment and completion by providing students with financial support (Perna & Elaine, 2017). These scholarships often provide children with money to pay for college when they reach college age. Children's Savings Accounts (CSAs) is another type of intervention that builds assets for children to use as long-term investments (Sherraden, 1991),

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particularly postsecondary education (Elliott & Harrington, 2016). Provided through financial institutions including state 529 college saving plans (e.g., Indiana's CollegeChoice) as well as banks and credit unions, CSAs generally include progressive features, such as initial deposits, savings matches, and/or other incentives (Goldberg, 2005; Sherraden, 1991). Unlike traditional scholarships, CSAs often distribute money into the children's account early on.

More recently, an increasing attention goes to combining traditional scholarships with CSAs. For example, the College Board (2013) recommended supplementing the Pell Grant program by opening savings accounts for children as early as age 11 or 12 who would likely be eligible for Pell once they reached college age and making annual deposits of 5% to 10% of the amount of the Pell Grant award for which they would be eligible. Such approach represents an early commitment large-scale scholarship program proposal that leverages the potential of CSAs. As the combined promise programs gain more attention, it is important to understand how combined scholarship and CSA program on children's academic performance. In this study, we examine combining scholarship programs designed to increase college attainment and savings for college with Children's Savings Accounts (CSAs) as a way to help, in particular, low-income children overcome barriers to college enrollment and completion. The following provides an overview of research on CSAs.

1.2. Review of research on CSAs and children's educational outcomes

Currently there are few studies that examine the relationship between CSAs and children's educational outcomes. This is because CSAs often start at birth, most of existing CSAs have started within the last ten years and the participating children are just becoming old enough to have academic records. As a result, most of the existing research discussed in this review relies on national data sets, and these studies use a proxy for participating in a CSA program. For example, Elliott (2009) uses bank savings as a proxy for having a CSA. More specially, Elliott (2009) has examined the association that children's savings with math scores of children, ages 12 to 18. Findings have 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-related purposes may be associated with improved children's math scores, even among children from households of similar income level. Moreover, findings have suggested that this relationship can partly be explained by the effects of children's savings on children's college expectations. These greater expectations subsequently encourage behavior that may be associated with greater achievement.

Family asset holdings may also influence how any type of children's savings account correlates to academic achievement. Elliott, Jung, and Friedline (2010) have examined how a child having any type of savings correlates with higher math scores, and found that the presence of savings for children, family net worth, and academic achievement are related in rather complicated ways. First, savings set aside for a child are positively associated with higher children's math scores. Moreover, such savings are positively related to higher achievement for children who live in low-wealth, middle-wealth, and high-wealth families. However, the presence of savings for a child is a stronger predictor of better math scores for children living in middle-wealth families than for children from low-wealth families, and the association with improved math scores is stronger yet for children living in high-wealth families than for children living in middle-wealth families. Overall, findings seem to indicate that children's savings may make an important independent contribution to children's math scores that is not explained solely by overall family wealth.

Unlike the previously cited study that only looked at the effect of the presence of any type of children's savings on math scores, the same authors have also examined the effect on math scores of a child having savings designated specifically for college (Elliott, Jung, & Friedline, 2011). They found that having savings designated for school is associated with higher children's math scores, and the effect does not vary by level of family wealth as it does when children have savings not specifically designated for college. This study implies that low-wealth children appear to benefit from having savings designated for school as much as high-wealth children do. On this basis, having savings designated for college—similar to most CSA programs—may be a better policy solution to promote improved academic achievement and achieve equity.

Family income was found playing a different role than family assets holding in affecting CSAs and its effects. Some studies suggest that there may be a threshold where, once a child's family income goes above a certain level, the relationship between college-designated savings and children's educational outcomes may disappear (e.g., Elliott, Constance-Huggins, & Song, 2013). This underscores the importance of CSAs in supporting low-income children who are able to equitably benefit from the intervention. More recently, Elliott, Kite, O'Brien, Lewis, and Palmer (2018) analyze achievement for the full sample of children and those eligible for free or reduced-price lunch. Results from the full sample revealed effects of CSAs were stronger for the subsample of students eligible for free or reduced priced lunch. For this group, having a CSA had a positive, statistically significant relationship with both reading and math scores. When considering amount saved on achievement, they found for every additional $100 contributed, reading scores increased by 2.08 units and math scores by 2.02 units. Overall, while current findings suggest that CSA show potential for improving children's performance in school, more research is needed.

1.3. How might a combined scholarship/CSA program improves educational outcomes

CSAs are savings vehicles that facilitate transformative wealth transfer, most commonly designed to help families with children to begin planning for college at the birth of a child or when the child begins kindergarten. Although they are meant to be universal programs that may be employed by all young people who aspire to postsecondary education, CSAs have specifically designed features that encourage savings among disadvantaged youths and their families. Usually deposits are permitted from children, their parents and other relatives, as well as from third parties, such as employers and scholarship programs. Ideally, these investments are leveraged with an initial “seed” deposit and/or matching funds that add public or philanthropic contributions to families' savings. For low-income savers, this offsets meaningful incentives that are already available to higher-income households through tax benefits and shifts the distribution of institutional resources more favorably toward these children.

Significantly, intervening early to initiate savings may afford not only greater financial asset accumulation but also cultivates educational expectations and engagement that can catalyze superior achievement. More specifically, some researchers have theorized that asset effects occur through a process known as institutional facilitation, whereby individuals' attitudes, expectations, and behaviors are shaped through interactions with supportive institutions such as CSAs (AEDI, 2013). In this case, when children experience a CSA program that reinforces a normative expectation of college attendance, their orientation towards academic achievement is bolstered, and they begin to act in ways congruent with their “college-bound” identity (e.g., Elliott, 2013; Oyserman, 2013). In turn, this leads to more savings, which further bolsters expectations and achievement (AEDI, 2013).

While the dimension of time is not the only characteristic of CSAs distinguishing them from other parts of the U.S. financial aid system, these long-term interventions do stand in sharp contrast to the “just-in-time” approach of student loans and even most merit- and needs- based grant aid. In the arena of educational attainment, there is real value in early initiation. Failure to plan for college enrollment from an early point in K–12 schooling is detrimental because the academic pathways to college, especially four-year colleges, are structured and sequential (e.g., Cabrera and La Nasa, 2000). For example, the track to college-level math begins in middle school, and fewer students from low-income families are likely to engage in college preparatory activities then because they do not *expect* to attend college even if they *aspire* to doing so (Long, Conger, & Iatarola, 2012; Lucas & Berends, 2002; Argys, Rees, & Brewer, 1996). Thus, to foster a sense that postsecondary education is a viable option for one's future, low-income students and their families may need to have a strategy for paying for college as early as possible.

1.4. Background of the combined scholarship/CSA program under study

The Wabash County Scholarships program is one example of how to leverage the potential of early-award financial aid and CSAs. Predating the creation of the Wabash County Promise Scholarship program in 2016 was the establishment of the Wabash County Promise in 2013. Now part of the state-supported and community-driven Children's Savings Account program known as Promise Indiana, the Wabash County Promise began with the Wabash County YMCA and local school leaders, who shared concerns about persistent disparities in educational attainment and low participation in the state's 529-college savings plan (CollegeChoice). The three principal components of the Promise Indiana CSA are (1) Facilitated enrollment in Indiana's 529 plan; 2) Financial incentives for family saving, including initial seed deposits, savings matches, and champion contributions; and 3) College and career planning activities, integrated into participating schools. In Wabash County, the CSA targets students in grades Kindergarten through third. Families opening a CollegeChoice 529 college savings plan through Promise Indiana complete a streamlined application process and receive a $25 account-opening incentive. Families are also eligible for matches to encourage contributions from their own resources or those that they secure from community ‘champions’. In addition to the account itself, children participate in college visit days and are exposed to early college planning and financial education content (see Elliott & Lewis, 2015 for a more detailed discussion of the origins and implementation of Promise Indiana). Families may begin the Wabash County Promise Scholarship program using an existing Promise Indiana 529 account, opened when their child was involved in the Wabash County Promise as a younger student, or they can open a 529 account for the specific purpose of being eligible for the scholarship awards. Similarly, families may simultaneously have younger children who are participating in the Wabash County Promise and older students receiving Wabash County Promise Scholarship awards.

The Wabash County Promise Scholarships program (Promise Scholars for short) provides financial awards to help students in grades 4 through 8 pay for college or career training after high school. Children receive these awards after meeting school engagement benchmarks, completing career and college readiness activities, and saving regularly in a Promise-affiliated Indiana CollegeChoice 529 college savings account. The program is available to all students in grades 4 through 8 across Wabash County, Indiana. Enrollment in the scholarship program requires ownership of an Indiana CollegeChoice 529 Direct Savings Plan and a signed Community Foundation Promise Scholarship participation agreement by which parents give permission for the release of program and academic data for purposes of awarding scholarships.

Families in Indiana may establish *Direct* or *Advised* accounts through Indiana's 529 plan administrator, Ascensus (CollegeChoice), or through a financial advisor. To participate in the Community Foundation Promise Early Award Scholarship Program, families must enroll in a Direct 529 Savings account and link it to the Wabash County Promise / Promise Early Award Scholarship Program. Families who have already enrolled in a CollegeChoice *Direct* Savings Account on their own, apart from any Promise program, may link the *Direct* account to the Wabash County Promise / Promise Early Award Scholarship Program. Families who established a CollegeChoice 529 Direct Savings Account as part of the Wabash County Promise for children in kindergarten through the 3rd grade will automatically be able to associate this account in the Promise Early Award Scholarship Program. In this study, *529* college savings accounts refer to those accounts that are both *Direct* and *linked* to the Wabash County Promise/Promise Early Award Scholarship Program. 529 college savings accounts that are established through a financial advisor (advised accounts) cannot be linked to the Wabash County Promise and are therefore not eligible to participate in the Program.

Once fully enrolled, fourth, sixth, and eighth-graders can earn multiple small scholarships for in-school learning, completing college and career readiness activities, and saving. Learning awards are linked less to achievements but more to behaviors that are likely to lead to progress toward postsecondary education. Fifth and seventh graders are only eligible for savings matches. Students in fourth, sixth, and eighth grades can earn as much as $100 per year for in-school activities completed with at least 70% proficiency and an additional $50 for savings matches, for a total of $150 in scholarship awards during each of the three grades. Fifth and seventh graders can earn $50 in savings matches each year.

1.5. CSAs component of Wabash County Promise Scholars

Student participants of Wabash County Promise Scholarships receive an initial $25 deposit when they open a Promise 529 college savings account for the first time and then are eligible for receiving savings matches when they contribute. Moreover, the Wabash County Promise Scholarship program seeks to activate families' preparation for their children's future postsecondary educations by guiding parents to start planning earlier in a child's life and encourage achieving academic and financial milestones. Similar to many CSAs, the Wabash County Promise Scholarship program seeks to cultivate ownership of early educational assets for their effects on children's prospects as well as on families' balance sheets.

2. Research questions

This research provides great understanding on the effect of financial policies and interventions on student outcomes in the education pipeline. However, another area of research that can contribute understanding in this area of scholarship are interventions that seek to build family assets and wealth in order to help parents cover cost for their children to attend college. Interventions that give students and their family College Saving Accounts (CSAs) is an emerging social policy intended to promote high academic achievement and increase access into higher education among low-income families. CSAs are long-term, incentivized savings or investment accounts for postsecondary education intended to influence college access, college affordability, and accruing financial wealth so that students are better positioned for success after they graduate from college (Elliott et al., 2018).

Although CSAs provides these benefits to children and families and potentially increase college access to date, there are not studies that examine the effects of combining CSAs with scholarships on children's educational outcomes. In order to fill this gap, this study examines the following related questions:

1) Do students participating in Promise Scholars have higher math and English scores on the ISTEP than students who are not in Promise Scholars?
2) Whether Promise Scholars' participants who have contributed to their account are associated with higher math and English scores on the ISTEP than Promise Scholars who have not contributed to their account?
3) Whether being a Promise Scholars' participant is associated with higher math and English scores on the ISTEP than being a CSA participant alone?

Table 1
Study comparison groups.

Group	Child Savings Account (CSA) Holder	Promise Scholarship Participant	Saving Contribution Made
No CSA (Comparison Group)	✗	✗	✗
CSA only	✓	✗	✗
Promise Scholars	✓	✓	✗
Promise Scholars Non-Savers	✓	✓	✗
Promise Scholars Savers	✓	✓	✓

3. Methods

3.1. Sample

The population for this study includes all 4th – 8th graders attending public school in Wabash County during the 2016–2017 academic year (N = 1942). Data provided by each of the three Wabash County school district included school name, grade, gender, free/reduced lunch eligibility (FRL), English Language Learner (ELL) status, and standardized test scores for Mathematics and Reading proficiency. School data were obtained for the current 2016–2017 school year as well as the prior 2015–2016 and 2014–2015 school years. Account data were provided from Ascensus College Savings, the provider of Indiana's CollegeChoice 529 Direct-Sold plan.

This data set included information about date of account opening and the date and type of each transaction. Promise Scholars program data were provided from program administrators and included data on quarterly scholarship and savings matches earned as well as goal setting and achievement for standardized assessments in English/Language Arts, Reading, and Mathematics. All cases in each dataset were assigned a unique ID by program staff. Merging of the three datasets (school, savings, and program) allowed for the creation of the three groups of interest: 1) Promise Scholars enrollees who by definition have a Promise Indiana or Promise Indiana-linked CSA; 2) Non-Promise Scholars enrollees with a CSA; and 3) those without a CSA. In the analyses that follow, these groups are referred to as Promise Scholars, CSA Only, and No CSA.

Forty-one percent of students were enrolled in the Wabash County Promise Scholarship program (n = 797) and 14% (n = 272) represent students with Promise Indiana savings accounts who were not enrolled in the Wabash County Promise Scholarship program. The remaining 873 (45%) are students without identifiable 529 accounts and not enrolled in the Promise Scholarship program.

3.2. Variable descriptions

3.2.1. ISTEP math and reading

Student achievement was assessed using English/Language Arts and Mathematics scores from the Indiana Statewide Testing for Educational Progress Plus (ISTEP+). ISTEP+ measures student achievement in English/Language Arts (referred to in this paper as reading proficiency) and Mathematics for grades 3 through 8 during the Spring semester. Although passing cut-off scores are available for each grade and subject, for the purposes of this paper, we use ISTEP+ scores as a continuous variable.

3.2.2. Goal setting

The Northwest Evaluation Association (NWEA) MAP assessments of Language Arts, Reading, and Math are conducted twice per year, allowing for measurement of individualized growth in academic achievement. At the beginning of the school year, each student sets a goal to meet for the Spring assessment. Meeting the goal in each subject was calculated as End Score ≥ Projected Score where 0 = did not meet goal; 1 = met goal.

3.2.3. Study groups

For this study, we created variables based on a combination of intervention status and saver status. Three groups represent possible intervention status: 1) Promise Scholars participants (Promise Scholars); 2) Students with a CSA but not in Promise Scholars (CSA Only); and 3) Students without a CSA (No CSA). Students in Promise Scholar program were further categorized as either Savers or Non-Savers. A Promise Scholar Saver is identified as those with CSA account where a saving contribution has been made in excess of programmatic incentives or match. In other words, Promise Scholar Savers are those had deposit made by the student or student's family during the time period of study. Those Promise Scholar participants did not make any saving contribution to their account were identified as Promise Scholar Non-Savers. Table 1 illustrates the five groups under study by their distinction on CSA holder, Promise Scholarship Participation, and Contribution.

3.3. Covariates

3.3.1. Grade

Student grade during each school year.

3.3.2. Gender

Dichotomous variable where 0 = Male; 1 = Female.

3.3.3. Free/reduced lunch status

Socioeconomic status was operationalized by whether or not a student receives a free or reduced-price lunch at school. This resulted in a dichotomous variable (0 = Paid, 1 = Free/Reduced). For purposes of this study, Free/Reduced Lunch is referred to as 'Poor' and Paid Lunch as 'Non-Poor'.

3.3.4. Special education status

Students meeting criteria for Special Education were identified with a dichotomous variable where 0 = not enrolled; 1 = enrolled.

3.3.5. ISTEP math and reading scores for the previous year

Student achievement was assessed using English/Language Arts and Mathematics scores from the Indiana Statewide Testing for Educational Progress Plus (ISTEP+). In all the models, the ISTEP scores from the previous year for entered into the model as a covariate. This is a step employed to address differences of treatments and controls in academic achievement in previous year which is considered baseline in the study, by matching cases on similar ISTEP scores in subject being investigated as the outcome.

Because of few variations exist in race and ELL status (over 90% of the sample were White and not ELL), these two variables were excluded from all analyses. Further, data from the 2014–2015 school year included many students who were not yet eligible for standardized testing as well as missing test scores that were not available to one of the three school districts, resulting in nearly 80% missing data. Thus, the 2014–2015 school year was excluded from as well.

3.4. Data analysis plan

Drawing causal inferences in observational studies is challenging particularly because observational studies often violate the ignorable treatment assignment assumption and selection bias is presumed to be present (Rosenbaum & Rubin, 1983). The problem of selection bias has led researchers to develop more rigorous and efficient analytical methods that can help evaluate treatment effects in studies based on observational data (e.g., Heckman, 1978, 1979; Rosenbaum & Rubin, 1983). One of the methods that has been developed to address selection bias is known as as propensity score analysis. Propensity score analysis aims to accomplish data balancing when treatment assignment is nonignorable; reduce multidimensional covariates to a one-dimensional score called a propensity score; and allow a more rigorous evaluation of treatment effects (Guo & Fraser, 2010). This study used propensity score analysis to correct for the effects of selection bias based on available covariates, and provide a rigorous estimation of the treatment effects (i.e., to test a potentially causal relationship, conditional on observed covariates, between participation in an asset-building program and wealth outcomes). Specifically, this study used propensity score optimal matching (Hansen, 2007; Haviland, Nagin, & Rosenbaum, 2007; Rosenbaum, 2002), and matching estimators (Abadie & Imbens, 2002, 2006) to estimate the hypothesized causal relationship. The main difference between the two approaches is that optimal matching is matching cases with similar propensity scores generated by logistic regression, matching estimators use a vector norm to calculate distance on the observed covariates between a treated case and each of its potential control cases and estimate various treatment effects (Guo & Fraser, 2010). In this study, matching estimators were used to cross validate the findings from optimal matching and identify different treatment effects.

3.5. Analysis framework

To draw valid causal inference, this study used the Neyman-Rubin counterfactual framework of causality (Neyman, 1923; Rubin, 1973, 1986). A counterfactual is defined as a potential outcome that would have happened in the absence of the cause (Shadish et al., 2002). Because the counterfactual is not observed in real data, the Neyman-Rubin framework holds that the researcher can assess the counterfactual by evaluating the difference in mean outcomes between the two groups (Guo & Fraser, 2010). Therefore, let $E(\Upsilon_o \mid W = 0)$, control group and $E(\Upsilon_o \mid W = 1)$, denote the mean outcome of the individuals in the treatment group. The treatment effect will be the mean difference: $t = E(\Upsilon_o \mid W = 1) - E(\Upsilon_o \mid W = 0)$. This formula is the standard estimator for the average treatment effect, which is the difference between two estimated means from the sample data (Guo & Fraser, 2010). In the current study, we examine the average score of ISTEP among the sample individual in the control group to address the issue of not observing the score for treated individual *i* in the condition of not having participated in the treatment. Therefore, if the difference between the two mean outcomes leads to $t = E(\Upsilon_o \mid W = 1) - E(\Upsilon_o \mid W = 0) > 0$, then the researcher can conclude that participation in the study causes higher ISTEP scores.

3.5.1. Propensity score optimal matching

We used optimal pair matching (i.e. each treatment participant matches to a single control) and full matching (each participant matches to a one or more controls and each control participant matches to one or more participants) to balance the data. We then performed Hodges-Lehmann aligned rank test to estimate the average treatment effect (ATE; Hodges & Lehmann, 1962). After we obtained the matched sample using optimal pair matching, we conducted a regression of difference scores with covariance control to estimate ATE (Rosenbaum, 2002; Rubin, 1979). We used imbalance indexes (Guo, 2009; Haviland et al., 2007) to check covariate imbalance before and after optimal matching. We conducted chi-square tests and independent sample *t*-tests to check the significance level of any covariate imbalance before matching.

3.5.2. Sensitivity analysis

Different assumptions and findings are required for each propensity score model in this study, which can result in findings being sensitive due to different data situations. To check the stability of our findings, we used the matching estimators methods to cross validate findings of optimal matching. Matching estimators allow for the estimation of different types of treatment effects. In the current study, we were interested in the average treatment effect for the treated (ATT). The ATT is used to determine if a program is beneficial for those assigned to the treatment or those who would assign themselves to the treatment (Winship & Morgan, 1999).

When we use the matching estimators as a sensitivity analysis tool, the SATT, PATT, SATE, and PATE are used to check the stability of the results. Matching estimators go beyond the features of conventional approaches to estimate the average treatment effects for the controls, treatment effects that include both sample and population estimates, variances and standard errors for statistical significance tests and a bias correction for infinite samples. The matching estimators allow evaluators to estimate effects for both the sample and the population. The SATE and PATE are used to address the difference. SATE is used to evaluate whether the program was successful. In contrast PATE is useful in evaluating if same program would be equally successful in a second sample from the population. A similar difference is true between SATT and PATT.

3.5.3. Matching estimators

Matching estimator methods were used to cross-validate the findings of optimal matching. Matching estimators match a treated case to a control or vice versa based on observed covariates. A vector norm is used to calculate distances on observed covariates between a treated case and each of its potential control cases (Abadie & Imbens, 2002, 2006). To assess the treatment effect on ISTEP scores, we included the same covariates used in optimal matching.

First, we used the bias-corrected matching method to remove bias caused by the three continuous-level covariates (Abadie & Imbens, 2002). We used the same set of matching variables as the independent variables for the regression adjusted in the bias correction process. We chose four matches per observation in the analysis following the recommendation of Abadie and associates (2004) Then we used the variance estimator allowing for heteroscedasticity because results of the Breusch-Pagan and Cool-Weisberg tests indicated three covariates violated the assumption of constant variance and used four matches again in the second matching stage to run the robust variance estimator.

4. Results

Table 2 presents sample distribution of ISTEP performance by key covariates. A majority of the sample was male students (51.99%, $n = 985$) with nonspecial education status (86.61%, $n = 1553$). Over a half (51%, $n = 916$) received free or reduced lunch. Study participants distributed rather evenly across five grade levels. Female students on average had higher math and reading scores than male students. Test scores vary by a student's grade, and students at higher-grade level on average scored higher on math and reading tests.

We also conduct analysis based on children's free and reduced lunch status. Table 3 shows ISETEP performance by key covariates and free or reduced lunch (FRL) status. Overall, students receiving FRL had lower test scores than students who did not receive FRL.

4.1. Tests of *Promise Scholars* program

In this section of the results, results from matching estimator analyses including six different average treatment effects of *Promise Scholars* (PS) participation on math and reading test scores of the full sample and the low-income sample are discussed. Specifically, Table 3 results indicate that, on average, those who did not participate in

Table 2
Sample distribution for aggregate sample.

	ISTEP			
	Math score		Reading score	
	n	Mean (SD)	n	Mean (SD)
Gender				
Female	898	516.08 (59)	895	529.42 (59)
Male	941	514.64 (63)	940	508.76 (62)
Grade				
3	359	465.17 (52)	355	482.79 (50)
4	349	503.42 (50)	349	507.15 (51)
5	338	525.18 (58)	338	523.69 (59)
6	333	529.14 (50)	333	537.86 (61)
7	371	556.33 (52)	371	547.55 (63)
Special education status				
Yes	220	464.88 (59)	219	458.61 (56)
No	1526	523.17 (57)	1523	528.66 (57)
Free/reduced lunch				
Yes	887	499.93 (59)	885	504.16 (61)
No	859	532.25 (58)	857	536.05 (59)

Promise Scholars (i.e., nonPS students with no CSA) had scores approximately 18 points lower on both math ($b = -18.37$, $p < .001$) and reading ($b = -18.86$, $p < .001$). As shown in Table 3, a specific sample effect is the same as its corresponding population effect in both direction and magnitude. For instance, both the sample average treatment effect (SATE) and the population average treatment effect (PATE) for math scores were about −18.37 points. Regarding the subpopulation of treated PS participants, the treatment effect was larger: −22.29 points or 3.92 points lower than SATE on match scores, and − 22.48 points or 5.62 lower than SATE on reading scores. Further, had all nonparticipants become *Promise Scholars* participants and had all PS participants not received PS with CSA intervention, then on average, the nonparticipants would have 14.42 points lower on match scores and 13.16 points lower on reading scores than their counterparts. In this study, the sample average treatment effect for the treated (SATT) equaled −22 points and the sample average treatment effect for the control (SATC) equaled −14 points, a difference of 8 points in match scores; the difference in reading scores between SATT and SATC is 11 points. Overall, the results consistently showed that *Promise Scholar* participants performed significantly better on math and reading tests.

Results on population effects indicated the *Promise Scholars* is likely effective in a second sample taken from the sample population (Guo & Fraser, 2010). As shown in Table 3, the SATT and PATT were statistically significant at a level of 0.001, suggesting that if we take a second sample from the population, we are likely to observe the same level of treatment effect for the treated, and the effect should remain statically significant at a level of 0.001 (Gup & Fraser, 2010). Finally, the results showed four treatment effects (SATE, PATE, SATT, and PATT) on math scores and reading scores were statistically significant ($p < .001$). These results indicate that, conditioned on the available data, *Promise Scholars* contributed to a higher score on math and reading.

4.1.1. Matching estimator results on low-income participants

Results from matching estimator analyses also showed PS participation had larger impact on the low-income participants than it had on the whole sample. As seen in Table 4, all six treatment effect coefficients yielded were larger among low-income sample than the full sample across all six different average treatment effects. For instance, results showed that nonparticipants on average scored 18.37 points lower than PS participants on math tests ($b_{SATE} = -18.37$, $p < .001$), whereas nonparticipants who were low-income students scored 19.19 points lower than low-income PS participants ($b_{SATE} = -19.19$, $p < .001$). As for the treatment effects for the treated (i.e., SATT and PATT), compared to low-income PS participants, low-income nonparticipants on average scored about 0.44 points lower on math tests ($b_{\mathrm{SATT}} = -22.73$, $b_{\mathrm{SATT}} = -22.29$; respectively). Similar results were found in the estimated average treatment effects for the control on math scores (e.g., $b_{\mathrm{SATC}} = -14.42$, $b_{\mathrm{SATC}} = -14.48$ for all PS participants and low-income participants, respectively).

Table 4 also shows the results from matching estimator regarding PS participation's effects on reading scores. All six average treatment effects coefficients of low-income participants were larger than they were on the whole sample, suggesting that PS participation had larger size of impact on low-income participants than it had on the average PS participant. In addition, differences in treatment effect coefficient between low-income sample and full sample were found larger on reading scores than it was on math scores. Take the results on SATE for example,

Table 3
Sample distribution by FRL status.

		ISTEP			
		Math score		Reading score	
		n	Mean (SD)	n	Mean (SD)
Gender					
Female	FRL	429	501.72 (56.48)	427	515.25 (57.52)
	Non-FRL	422	531.82 (56.61)	421	545.77 (58.17)
Male	FRL	458	498.24 (61.52)	458	493.84 (61.56)
	Non-FRL	437	532.66 (59.02)	436	526.66 (57.34)
Grade					
3	FRL	189	453.35 (51.85)	187	472.95 (50.01)
	Non-FRL	170	478.31 (47.94)	168	493.75 (48.33)
4	FRL	172	488.20 (47.46)	172	490.52 (49.40)
	Non-FRL	177	518.22 (47.43)	177	523.30 (46.95)
5	FRL	184	509.54 (55.23)	184	510.34 (57.91)
	Non-FRL	154	543.86 (54.79)	154	539.64 (55.92)
6	FRL	161	511.85 (48.57)	161	518.14 (60.14)
	Non-FRL	172	545.33 (46.60)	172	556.33 (56.60)
7	FRL	180	539.44 (53.72)	180	530.66 (66.33)
	Non-FRL	186	573.19 (44.22)	186	564.67 (55.56)
Special education status					
Yes	FRL	154	455.34 (57.93)	153	448.77 (51.83)
	Non-FRL	66	487.15 (54.77)	66	481.42 (58.09)
No	FRL	733	509.29 (54.99)	732	515.75 (55.68)
	Non-FRL	793	536.00 (56.49)	791	540.61 (56.22)

Table 4
Estimated average treatment effects of promise scholars: results from the matching estimator on full sample and low-income subsample.

Treatment effects	IESTEP			
	Math scores*		Reading scores**	
	Coefficient (SE)		Coefficient (SE)	
	Full sample (N = 1507)	Low-income (n = 737)	Full sample (N = 1507)	Low-income (n = 735)
SATE	−18.37 (2.70)***	−19.19 (3.85)***	−18.86 (3.08)***	−23.15 (4.05)***
PATE	−18.37 (2.70)***	−19.19 (3.85)***	−18.86 (3.08)***	−23.15 (4.49)***
SATT	−22.29 (3.05)***	−22.73 (4.35)***	−24.48 (3.76)***	−28.10 (5.52)***
PATT	−22.29 (3.05)***	−22.73 (4.34)***	−24.48 (3.75)***	−28.10 (5.50)***
SATC	−14.42 (3.06)***	−14.48 (4.31)***	−13.16 (3.27)***	−16.52 (4.46)***
PATC	−14.42 (3.08)***	−14.48 (4.35)***	−13.16 (3.25)***	−16.52 (4.42)***

Note. SATE = Sample Average Treatment Effect, PATE = Population Average Treatment Effect, SATT = Sample Average Treatment Effect for the Treated, PATT = Population Average Treatment Effect for the Treated, SATC = Sample Average Treatment Effect for the Control, PATC = Population Average Treatment Effect for the Control. *SE* = standard error. Matching variables are gender, grade, special education status, and recipient of free or reduced lunch. N = 1511.
* $p < .10$.
** $p < .05$.
*** $p < .001$.

difference in coefficients between low-income participants and all PS participants was 4.29 points on reading scores ($b_{\text{SATC}} = -23.15$, $b_{\text{SATC}} = -18.86$, respectively) and 0.82 on math scores ($b_{\text{SATC}} = -19.19$, $b_{\text{SATC}} = -18.37$, respectively).

Table 5 shows the estimated average treatment effects estimated on the whole sample as well as the low-income subsample using three different statistical methods. Results yielded from matching estimators and unadjusted OLS regression had similar variation in the magnitude of ATE coefficients, direction of the intervention's effect, and level of statistical significance. As expected, the ATT effects estimated from using Kernel-based matching were larger than the ATE estimates (See Table 4). In addition, the coefficients yielded from matching estimator and OLS regression were approximately 0.21 to 4.29 points larger when analyses were restricted to the low-income subsample.

4.2. Test of saving effect of Promise Scholars

To examine the effects of the saving component of the *Promise Scholars*, matching estimators were used to compare two sets of groups on their math scores and reading scores. First, matching estimators' analyses were employed to estimate the savings effect by comparing *Promise Scholar* participants who contributed to savings (PS Savers) and those did not contribute (PS nonSavers). As demonstrated in Table 6, comparing math scores, five out six treatment effects showed that, on average, PS Savers scored approximately 10 points higher than PS nonSavers. On reading scores, PS Savers performed about 9 points higher than the PS nonSavers, but the differences were not statistically significant. When analyses were constricted to the low-income participants, results showed that low-income PS Savers scored about 6.81 to 9.53 points higher on math tests than those low-income PS nonSavers, but differences were not statistically significant across all treatment effects. As for saving effects on reading scores, coefficients yielded from the average treatment effects for the treated were significant, suggesting that low-income PS Savers performed −12.53 higher than PS nonSavers. The other average treatment effects (i.e., SATE, PATE, SATC, PATC) were not statistically significant.

Table 7 shows results from matching estimator analyses that were performed to compare the PS Savers and study participants who did not have any CSA (nonCSA). Results on the full sample across all six treatment effects showed that PS Savers scored approximately 17 to 29 points higher on math test and 15 to 31 points higher on reading test than nonCSA students. The estimated average treatment effects for the treated (i.e., SATT and PATT) had the highest coefficients on math and reading scores, followed by average treatment effects (SATE and PATE).

Table 5
Estimated average treatment effects: results from the matching estimator and unadjusted ordinary least square (OLS).

Test statistics	Estimated average treatment effects			
	Math scores		Reading scores	
	Full sample**	Low-income	Full sample	Low-income
Matching Estimators	−18.37***	−19.19***	−18.86***	−23.15***
Unadjusted OLS Regression	−18.78***	−18.99***	−18.78***	−21.50***
Kernel-based Matching (ATT)	−24.69*	−22.65*	−27.55*	−22.65*

* $p < .10$.
** $p < .05$.
*** $p < .001$.

Table 6
Estimated average treatment effects of savings: results from the matching estimator comparing PS savers and PS nonSavers.

Treatment effects	PS savers vs PS nonSavers			
	Math scores		Reading scores	
	Coefficient (SE)		Coefficient (SE)	
	Full sample (n = 752)	Low-income (n = 318)	Full sample (n = 748)	Low-income (n = 314)
SATE	−9.80 (3.56)**	−8.13 (5.45)***	−9.07 (3.74)	−10.67 (5.67)
PATE	−9.80 (3.52)**	−8.13 (5.37)	−9.07 (3.72)	−10.67 (5.59)
SATT	−10.06 (3.64)**	−9.53 (5.46)	−9.51 (3.83)	−12.53 (5.71)*
PATT	−10.06 (3.54)**	−9.53 (5.31)	−9.51 (3.78)	−12.53 (5.60)*
SATC	−9.62 (3.73)	−6.81 (5.77)	−8.78 (3.92)	−8.95 (6.01)
PATC	−9.62 (3.67)**	−6.81 (5.62)	−8.78 (3.89)	−8.95 (5.84)

Note. SATE = Sample Average Treatment Effect, PATE = Population Average Treatment Effect, SATT = Sample Average Treatment Effect for the Treated, PATT = Population Average Treatment Effect for the Treated, SATC = Sample Average Treatment Effect for the Control, PATC = Population Average Treatment Effect for the Control.
* $p < .10$.
** $p < .05$.
*** $p < .001$.

Table 7
Estimated average treatment effects of savings: results from the matching estimator comparing PS savers and nonCSA participants.

Treatment effects	PS savers vs nonCSA			
	Math scores		Reading scores	
	Coefficient (SE)		Coefficient (SE)	
	Full sample (n = 1215)	Low-income sample (n = 584)*	Full sample (n = 1213)	Low-income sample (n = 584)
SATE	−24.64 (3.25)***	−27.83 (5.03)***	−25.20 (3.67)***	−34.20 (5.71)***
PATE	−24.64 (3.26)***	−27.83 (5.05)***	−25.20 (3.68)***	−34.20 (5.73)***
SATT	−29.09 (3.81)***	−32.16 (5.70)***	−31.05 (4.44)***	−39.40 (6.63)***
PATT	−29.09 (3.81)***	−32.16 (5.72)***	−31.05 (4.45)***	−39.40 (6.65)***
SATC	−17.23 (3.55)***	−16.66 (5.19)**	−15.42 (3.76)***	−20.78 (5.45)***
PATC	−17.23 (3.57)***	−16.66 (5.20)**	−15.42 (3.72)***	−20.78 (5.31)***

Note. SATE = Sample Average Treatment Effect, PATE = Population Average Treatment Effect, SATT = Sample Average Treatment Effect for the Treated, PATT = Population Average Treatment Effect for the Treated, SATC = Sample Average Treatment Effect for the Control, PATC = Population Average Treatment Effect for the Control.

* $p < .10$.

** $p < .05$.

*** $p < .001$.

The estimated average treatment effects for the control (SATC and PATC) had the smallest coefficients. These results suggest that, conditioned on the available data, the saving component of the *Promise Scholars* contributed to a higher math score and a higher reading score among students in the treatment conditions.

4.2.1. Saving effects on low-income subsample

Results also showed that low-income PS Savers scored about 16 to 32 points higher on math tests and about 20 to 39 points higher than low-income nonCSA study participants. A comparison between the full sample and the low-income subsample suggests that estimated average treatment effects of savings were larger on test scores of low-income participants than those of the full sample.

4.3. Does Promise Scholars add to CSA model?

One focus of this study was to investigate whether *Promise Scholars* exerts additional effects beyond current CSA model. To address this question, matching estimators were employed to compare match and reading scores between PS participants and CSA participants (See Table 7). Given that all PS participants had CSA ownership, the estimated treatment effects should be interpreted as the effects of all programming elements except CSA ownership of the *Promise Scholars*. As see in Table 8, compared to CSA participants, PS participants scored approximately 17 to 25 points higher on math tests and 14 to 18 points on reading tests. The effect sizes across all six treatment effects were noticeable large and significant at the level of 0.001. Additionally, results on the low-income samples showed that low-income PS participants scored 18 to 21 points higher on math tests and 12 to 19 points higher on reading tests than low-income CSA only participants. A comparison of coefficients of the average treatment effects over the full sample and low-income subsample suggests that the PS CSA intervention had larger size of effects on the low-income participants than it had on the full sample on average.

Matching estimators were also used to estimate the effects of CSA program on math and reading test scores (See Table 9). Results showed that there were no statistically significant differences on match and reading scores between CSA participants and CSA nonparticipants across all six treatment effects. Due to the small sample size of low-income participants with CSA only and those with no CSA, matching estimator was not performed on the subsample.

5. Discussion

While more city and states are looking to Children's Savings Accounts (CSAs) to help improve children's educational outcomes, more

Table 8
Estimated average treatment effects of PS and CSA intervention: results of the matching estimators.

Treatment effects	PS CSA vs CSA only			
	Math scores		Reading scores	
	Coefficient (SE)		Coefficient (SE)	
	Full sample (n = 986)	Low-income sample (n = 465)	Full sample (n = 986)	Low-income sample (n = 463)
SATE	−19.21 (3.72)***	−21.09 (4.88)***	−15.23 (3.80)***	−13.99 (4.92)**
PATE	−19.21 (3.73)***	−21.09 (4.87)***	−15.23 (3.78)***	−13.99 (4.89)**
SATT	−25.06 (3.84)***	−25.74 (5.00)***	−18.71 (3.75)***	−17.74 (4.79)***
PATT	−25.06 (3.85)***	−25.74 (4.88)***	−18.71 (3.69)***	−19.14 (4.88)***
SATC	−17.39 (3.89)***	−18.89 (5.19)***	−14.14 (4.02)***	−12.21 (5.34)*
PATC	−17.39 (3.90)***	−18.89 (5.18)***	−14.14 (4.01)***	−12.21 (5.20)*

Note. SATE = Sample Average Treatment Effect, PATE = Population Average Treatment Effect, SATT = Sample Average Treatment Effect for the Treated, PATT = Population Average Treatment Effect for the Treated, SATC = Sample Average Treatment Effect for the Control, PATC = Population Average Treatment Effect for the Control.

* $p < .10$.

** $p < .05$.

*** $p < .001$.

Table 9
Estimated average treatment effects of PS and CSA intervention: results of the matching estimators.

Treatment effects	CSA only vs No CSA	
	Math scores	Reading scores
	Coefficient (SE)	Coefficient (SE)
SATE	−1.17 (4.41)*	6.92 (4.64)
PATE	−1.17 (4.42)**	6.91 (4.65)
SATT	−5.33 (4.02)***	−1.33 (3.82)
PATT	−5.33 (4.05)	−1.33 (3.84)
SATC	0.11 (4.92)	9.46 (5.26)
PATC	0.11 (4.93)	9.46 (5.26)

Note: SATE = Sample Average Treatment Effect, PATE = Population Average Treatment Effect, SATT = Sample Average Treatment Effect for the Treated, PATT = Population Average Treatment Effect for the Treated, SATC = Sample Average Treatment Effect for the Control, PATC = Population Average Treatment Effect for the Control.

* $p < .10$.

** $p < .05$.

*** $p < .001$.

recently, however, there has been an effort to combine CSA programs with scholarship programs (Elliott & Levere, 2017). In this paper, we examine the Wabash County Promise Scholarship program. It is a scholarship program which reallocates small amounts of money typically given to students as a scholarship once admitted into a postsecondary institution, and instead, puts it into a CSA much earlier (e.g., during elementary, junior high, or high school). Until now, there has not been the opportunity to test whether combining CSAs with a Promise program is an effective strategy for improving children's educational outcomes. Specifically, this study examines whether students participating in Promise Scholars have higher math and reading scores on a state assessment test, whether being a participant who contributed to their CSA account raises scores, and whether being a participant is associated with higher math and reading scores than being a CSA participant alone.

Findings from this study showed that participants in the Promise Scholars program have significantly higher math and reading scores than students who did not participate in Promise Scholars. These finding are robust against sensitivity analysis. Given that no other studies have examined a combined CSA and scholarship program, the question becomes how this research compares to previous findings on standalone CSA programs. Findings from existing research on CSA only programs and its effects on math and reading performance are mixed. Studies that use savings in a bank account as a proxy for taking part in a CSA program typically find a positive, significant relationship with children's educational outcomes (e.g., Elliott, 2009). In contrast, using data from a CSA program, Elliott et al. (2018) find little evidence that mere participation in the CSA program is significantly related to math or reading scores when examining the full sample (i.e., not separating out low-income children) of participants. Differences might stem from the fact that, unlike traditional standalone CSA programs, the Promise Scholarship program provides financial incentives specifically designed to improve children's educational outcomes. Research shows that financial incentives directed at "inputs" as opposed to "outputs" can be particularly effective at improving children's performance in school (Fryer, 2011, p. 9). Allan and Fryer (2011) define inputs as, "anything that can contribute to student learning", outputs are outcomes such as test scores (p. 9). Promise Scholar provides incentives for doing school learning activities and completing college and career readiness activities, inputs. In line with this, this study finds when children who have both a CSA and a scholarship are compared to children who only have a CSA, children who also have the scholarship have higher math and reading scores than children with only a CSA.

This study also found that being a saver is associated with children's math scores but not their reading scores, which contradicts with findings from Elliott et al. (2018)'s study that being part of a CSA program and being a saver (i.e., contributing to the account) is associated with improved reading scores but not math scores. Such discrepancy may due to the fact that the program under study of Elliott et al. (2018) did not have a scholarship component, and participants were younger than those in current study. However, both studies found significant, positive association between program participation and educational outcomes when examining low-income children. Such finding that effects of CSAs are consistent and stronger among low-income families is also observed in other studies (e.g., Huang, Sherraden, Kim, & Clancy, 2014).

5.1. Limitations

This study has several limitations important to point out. Findings from this study cannot be generalized to a larger population given that the sample only includes families in Wabash County, and most participants are white. Although rigorous analytical approaches are used to address selection bias, our findings regarding the relationships between promise scholar participation and educational outcomes cannot fully rule out other explanation for findings. Unobserved differences between matched groups is impossible to rule out, as it is one of the inherent limitations in using propensity score analysis. In addition, because the study focused on administrative data, we were unable to control for a wide variety of parental and child characteristics. However, while more research is needed, this study provides unique data and a rare opportunity to further the discussion about the potential of combining early award scholarships with CSA programs for improving children's educational outcomes.

6. Conclusion

Despite mixed evidence regarding the effects of CSA only programs on children's math and reading scores, this study provides evidence that the Promise Scholar program, which combines CSAs with scholarships, has a positive association with children's math and reading scores in Wabash County, IN. This suggests that existing CSA programs aiming at improving children's educational outcomes may benefit from including financial incentives targeted at educational activities. The policy of combining CSAs with scholarship programs is strengthened when considering evidence of savings participation in the Promise Scholars program. O'Brien, Elliott, Leiws, and Jung (2018) find that while low-income families save at lower rates than their higher income counterparts do, they participate in the scholarship component at identical or higher rates than their higher income counterparts do. This suggests that low-income families are likely to participate in scholarship programs as a way of building assets for their kids to attend college even if they lack the money to save, at least in Wabash County, IN.

Further, the current study suggests that engagement in scholarship programs has additional effects beyond building assets; it also has the potential of improving children's math and reading scores. This potential for educational effects might also provide support for combining programs such as the Pell Grant program with CSAs as proposed by the College Board (2013). The College Board (2013) recommended supplementing the Pell Grant program by opening savings accounts for children as early as age 11 or 12. Doing so might produce both educational and wealth effects over the course of a child's life, not just when they reach college age.

In addition, the effects of the Promise Scholar program, similar to previous findings on CSA only programs, are strongest among low-income children. This should not be surprising given that higher income children have fewer reasons to doubt their ability to pay for college when compared to lower income families. As a result, what amounts to a small dollar CSA is less likely to influence their engagement in school. The stronger effects among low-income families raises questions about whether CSA programs may best serve as an intervention for low-income children, not higher income children. While rigorous research designs are needed to pin down the causal relationship between CSA and test scores, the current study serves a starting point and its findings suggest targeting CSA resources on low-income families may yield desired outcomes therefore can be a potential approach for promoting college access and completion.

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