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Small-Dollar Children's Savings Accounts, Income, and College Outcomes

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Small-Dollar Children's Savings Accounts, Income, and College Outcomes

In this paper, we examine the relationship between children's small-dollar savings accounts and college enrollment and graduation by asking three important research questions: (a) are children with savings of their own more likely to attend or graduate from college, (b) does dosage (having no account; having basic savings only; or having savings designated for school of less than $1, $1 to $499, or $500 or more) matter, and (c) is designating savings for school more predictive than having basic savings alone? We use propensity score weighted data from the Panel Study of Income Dynamics (PSID) and its supplements to create multi-treatment dosages of savings accounts and amounts to answer these questions separately for children from low- and moderate-income (LMI) (below $50,000; N = 512) and high-income (HI) ($50,000 or above; N = 345) households. We find that LMI children may be more likely to enroll in and graduate from college when they have small-dollar savings accounts with money designated for school. An LMI child with school savings of $1 to $499 before college age is more than three times more likely to enroll in college than an LMI child with no savings account and more than four and half times more likely to graduate. In addition, an LMI child with school savings of $500 or more is about five times more likely to graduate from college than a child with no savings account. Policy implications also are discussed.

Key words: *saving, asset-building, wealth accumulation, low-income, child development accounts, children's savings accounts, educational outcomes, college savings, college enrollment, college graduation, small-dollar accounts*

Highlights

- Only 27% of HI children do not have savings accounts contrasted with 61% of LMI children.
- Findings from this study indicate the following percentages of LMI children graduate from college: 5% of those with no accounts, 25% of those with school savings of $1 to $499, and 33% of those with school savings of $500 or more.
- Overall, findings suggest that having even a small amount of savings designated for school (e.g., $1 to $499) can have a positive effect on LMI children's graduation rates:
    - An LMI child with school savings of $1 to $499 before reaching college age is more than four times more likely to enroll in college than a child with no savings account.
    - An LMI child with school savings of $500 or more is about five times more likely to graduate from college than an LMI child with no savings account.

Introduction

Since the 1980s, the United States has failed to produce college graduates to keep pace with demand for skilled workers (Carnevale & Rose, 2011). Researchers at the Center on Education and the Workforce at Georgetown University forecast that 63% of all jobs will require some college coursework by 2018 and a shortfall of 300,000 college graduates per year through 2018 (Carnevale, Smith, & Strohl, 2010). The US formerly led all developed countries in producing college graduates, but by 2008 had dropped to seventh place (Carnevale & Rose, 2011).

The percentage decline of college graduates as a proportion of America's working age population represents a loss of potential earning and spending power for individuals, families, and the country as a whole. At the macro level, education has been linked to increased tax revenues, greater productivity, increased consumption of goods, increased workforce flexibility, and decreased reliance on government assistance (Institute for Higher Education Policy [IHEP], 2005; see also Baum, Ma, & Payea, 2010). On average, individuals with a bachelor's degree earn 74% more than individuals with a high school diploma only (Carnevale & Rose, 2011).

Balancing Individual and Societal Interests

Although college education is important to individuals and society, the trend in financial aid policy has been to shift more of the financial responsibility to the individual. Since the late 1970s, the federal government has attempted to solve the problem of prohibitive college costs by adopting policies that make college loans more accessible (e.g., Stafford subsidized and unsubsidized loan programs). The Middle Income Student Assistance Act (1978) made college loans more accessible by removing the income limit for participation in federal aid programs (Hansen, 1983). The Higher Education Act (1992) made unsubsidized loans available, and the Budget Reconciliation Act (1993) included provisions for the Federal Direct Loan Program. More recently, Congress raised the ceiling on the amount of individual federal Stafford loans students can borrow through the Ensuring Continued Access to Student Loans Act of 2008. As these policy changes have made loans more abundant, the number of federal grants has plummeted. The proportion of federal grants to federal loans in 1976 was almost even (Archibald, 2002), but by 1985, the ratio had shifted to 27% grants to 70% loans. By 1998, it shifted further to 17% grants to 82% loans (Archibald, 2002; see also Heller & Rogers, 2006).

A financial aid system overly dependent on loans requires students and their families to bear a heavy burden to pay for college because the majority of loans must be paid back with accrued interest. This financial burden may be making the American Dream less attainable. From academic years 2007–08 to 2008–09, total education borrowing increased by 5% (i.e., $4 billion) (Steele & Baum, 2009).[1] Among students who received educational loans and graduated from four-year public universities in 2007–08, the median debt was $17,700, a 5% increase from the educational debt of similar students in 2003–04 (Steele & Baum, 2009). Moreover, 10% of students who received educational loans and graduated in 2007–08 had more than $40,000 of debt (Steele & Baum, 2009). At four-year private colleges, the median loan debt of those holding undergraduate degrees was $22,375 in 2007–08, a 4% increase from 2003–04. Among those holding undergraduate degrees from four-year private colleges, 22% had more than $40,000 in debt (Steele & Baum, 2009).

[1] These figures include federal loans only, not other types of borrowing for school, such as credit cards or personal loans.

Mounting student debt may weaken the belief in education as a viable path to the American Dream of working hard to build a better life—a central driver in the history and life of our nation—which is associated with the constitutional right of all citizens to the "pursuit of happiness" (American Student Assistance, 2010). In its simplest form, the American Dream is the belief that effort and ability allow for success. Striving to attain it is essential to maintaining a motivated work force and citizens' support for the country's rules and regulations.

Few organizations have been more important in sustaining the American Dream than public educational institutions, including colleges and universities. Education has been called the "great equalizer," evoking the widespread belief that disparities among groups of people can be narrowed through effort in school and the pursuit of higher education. As such, the entire nation has a stake in making sure that all citizens continue to view college attendance and graduation as a viable way to achieve the American Dream. Today, the opportunity to succeed increasingly depends on children having access to college, which includes having enough money to prepare for, enroll in, and graduate from college.

Assets for children – a strategy for balancing individual and collective interests

Policymakers and researchers have begun to question whether having students acquire massive amounts of debt to fund their education is wise policy (e.g., Baum, 1996). The current economic crisis and focus on debt may make children's savings policies a more appealing alternative to expanding access to college loans. Financial aid policies that promote asset accumulation among children and their families are a way for the federal government to help restore balance in the financial aid system. Unlike student loans, asset accumulation tools—including Children's Development Accounts (CDAs)—compound individual and family investments with investments from the federal government (e.g., initial deposits, incentives, savings matches). The proposed ASPIRE (American Savings for Personal Investment, Retirement, and Education) Act is an example of a program that would seed CDAs with initial contributions of $500 or more for the most disadvantaged people and provide opportunities for financial education and incentives. Accountholders would be permitted at age 18 to make tax-free withdrawals for costs associated with post-secondary education, first-time home purchase, and retirement security.

The ASPIRE Act has not been passed into law, but similar efforts to create a more accessible savings infrastructure for children are underway. State college savings (529) plans are tax-advantaged savings vehicles offered in 49 states and the District of Columbia. Savings in 529s grow free from federal and state taxation in many cases. Often these plans offer limited benefits for low- and moderate-income families, but some states have implemented savings match programs and other benefits for those savers.[2] Knowledge gained from the collective 529 experience will allow states to learn more about the relationship between savings and educational outcomes and eventually may pave the way toward adoption of a national CDA policy.

Popular educational savings accounts (e.g., Coverdell Education Savings Accounts, Uniform Gifts to Minors Act [UGMA], 529 college savings plans, and Roth Individual Retirement Arrangements [IRAs]) offer their owners protection from taxation, and some have infrastructure that allows for direct deposit and provide savings matches to encourage savings. Savings in these accounts typically

[2] See Lassar, Clancy, & McClure (2011).

cannot be withdrawn without taxes or penalties until youth reach college age, and withdrawals must be spent on college-related expenses. As a result, these accounts can be defined as non-liquid. Unlike users of these popular education accounts, children in this study can withdraw and use money from their accounts without penalty, but they do not benefit from tax breaks or other incentives that are common components of CDAs (e.g., initial deposits or savings matches provided by the federal government or another agency).

Research Questions

The following three research questions flow out of the theoretical framework outlined in Elliott (2012) and Elliott, Destin, and Friedline (2011) and were asked separately for LMI and HI children: (a) are children with savings of their own more likely to attend or graduate from college, (b) does dosage (having no account; having basic savings only; or having designated savings for school of less than $1, $1 to $499, or $500 or more) matter, and (c) is designating savings for school more predictive than having basic savings alone?

Methods

Data

This study uses longitudinal data from the PSID and its supplements, the Child Development Supplement (CDS) and the Transition into Adulthood (TA) Study. The PSID, a nationally representative longitudinal survey of U.S. individuals and families, began in 1968 and collects data on employment, income, and assets. The CDS was administered to 3,563 PSID respondents in 1997 to collect a wide range of data on parents and their children aged birth to 12 years. It focuses on a broad range of developmental outcomes across the domains of health, psychological well-being, social relationships, cognitive development, achievement motivation, and education. Follow-up surveys were administered in 2002, 2007, and 2009. The TA Study administered in 2005, 2007, and 2009 measured outcomes for young adults who participated in earlier waves of the CDS and were no longer in high school.

The three data sets were linked using PSID, CDS, and TA map files containing family and personal ID numbers. The linked data sets provide a rich opportunity for analyses in which data collected at earlier points in time can be used to predict outcomes, and stable background characteristics can be used as covariates. Even though the PSID initially oversampled low-income families, we do not use sampling weights in this study because the sample is divided by income levels. Weights become unusable once subsamples are investigated.

Sample data

The 2009 TA sample consisted of 1,554 participants. The sample in this study was restricted to Black and White children because only small numbers of other racial groups exist in the TA. The sample also was restricted to children who were 14 to 19 years old in 2002 so they would be old enough to have graduated college by 2009. Our final sample consists of 857 children and their families. We divided the sample into an LMI (below $50,000; n = 512) sample and an HI ($50,000 or more; n = 345) sample (Table 1).

Variables

The variable of interest in this study is children's savings, created using 2002 CDS data. The CDS asks children between the ages of 12 and 18 whether they have a physical savings or bank account in their name. The children's basic savings variable divides children into two categories: (1) those who had an account in 2002, and (2) those who did not. Children with accounts were asked whether they were saving some of this money for future schooling (i.e., whether they had mentally set aside some savings for school). Children who replied yes were asked the amount of savings they have for future schooling between $.01 and $9,997.99. Using the two children's savings variables and the amount saved for school variable, we created five treatment groups, or doses, similar to Imbens' (2000) multiple-dose treatment approach (see also Guo & Fraser, 2010). The doses are children with (a) no savings, (b) basic savings only, (c) school savings of less than $1, (d) school savings of $1 to $499, and (e) school savings of $500 or more.

Outcome Variables

The two outcome variables in this study are college enrollment and college graduation. College enrollment was operationalized as whether or not a child had ever enrolled in college by 2009 (1 = yes; 2 = no). College graduation measures whether a child graduated from college (yes = 1; no = 0). In this study, college refers to either a two- or four-year college.

Control Variables

There are 11 control variables used in this study, including child's age in 2002, child's race (1 = Black; 0 = White), child's gender (female = 1; male = 0), child's academic achievement, head of household's marital status in 2003 (1 = married; 0 = not married), head of household's education level in 2003, household size in 2003 (continuous variable), region of the country in which the family lived in 2003, log of household income, inverse hyperbolic sign of household net worth, and log of liquid assets.

Log of household income. The log of household income was created using income variables from 1989, 1994, 1999, 2004, and 2009 and inflated to 2009 price levels using the Consumer Price Index (CPI). Income variables were averaged across all five years, and average income was transformed using the natural log transformation to account for the skewedness of the variable.

Inverse hyperbolic sine of household net worth. Household net worth is a continuous variable that sums all assets, including savings, stocks/bonds, business investments, real estate, home equity, and other assets and subtracts all debts, including credit cards, loans, and other debts as reported in the 1989, 1994, 1999, and 2001 PSID. We use the inverse hyperbolic sine (IHS) transformation (Kennickell & Woodburn, 1999), which allows for the existence of negative values and more clearly demonstrates changes in wealth distribution. The natural log transformation does not.

Log of family liquid assets. In addition to family net worth, we include the value of all liquid assets from savings accounts, stocks, or bonds from the 1989, 1994, 1999, and 2001 PSIDs because these assets can be turned easily into cash to pay for college costs. Net worth includes illiquid assets such as home equity that cannot be turned easily into cash. Liquid assets do not include debts and thus have no negative values. Therefore, we use the natural log transformation to account for skewedness.

Head of household's education level. In the PSID, the head of household's education level is a continuous variable (1–16) with each number representing a year of completed schooling.

Region. This variable captures the region in which a child's family lived at the time of the 2003 interview, including the Northeast, North Central, South, and West regions of the country. Northeast includes Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. North Central includes Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. South includes Alabama, Arkansas, Delaware, the District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, Washington, and West Virginia. West includes Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming. The Northeast region is the reference group for this study.

Academic achievement. This is a continuous variable that combines math and reading scores. The Woodcock Johnson (WJ-R), a well-respected measure, is used by the CDS to assess math and reading ability (Mainieri, 2006). In descriptive analysis, we use a dichotomous variable indicating whether children had average, above-average, or below-average achievement. Average and above-average achievement are coded 1, and below-average achievement is coded as 0.

Child's age. Age in 2002 is a continuous variable. In the descriptive analysis, a dichotomous variable indicates whether children were 16 years old or younger (coded as 0) or older than 16 years (coded as 1) in 2002.

Analysis plan

We conducted four stages of analysis in this study. In stage one, we completed missing data using the *da.norm* function in R (R Development Core Team, 2008), which simulates one iteration of a single Markov chain regression model. The iteration consists of a random imputation of the missing data given the observed data and current parameter value, followed by a draw from the parameter distribution given the observed data and imputed data (Shafer, 1997). Missing data can lead to inaccurate parameter estimates and biased standard errors and population means, resulting in inaccurate reporting of statistical significance or non-significance (Graham, Taylor, & Cumsille, 2001).

Remaining analyses was conducted using STATA version 12 (STATA Corp, 2011). In stage two, we conducted propensity score weighting with multi-treatments/dosages in order to balance selection bias between those who were exposed to having savings and those who were not, based on known covariates (Guo & Fraser, 2010; Imbens, 2000). More specifically, we created five groups: (a) children with no savings; (b) children with basic savings only; (3) children with school savings of less than $1; (d) children with school savings of $1 to $499; and (e) children with school savings of $500 or more. Next we estimated a multinomial logit regression that predicted multi-group membership using the 11 covariates in this paper. All variables were included in the multinomial logit regression because all had a positive correlation with the outcome variables (Guo and Fraser, 2010). The resulting coefficient estimates were used to calculate propensity scores for each group. The inverse of that probability was used to create the propensity score weight.

In stage three, we tested covariate imbalance after weighting. Since propensity score weighting does not use matching, we ran a weighted simple logistic regression or an ordinary least squares (OLS) regression depending on whether the dependent variable (i.e., child's age, race, gender, academic achievement, head of household's marital status, head of household's education level, household size, region lived in, log of family income, IHS net worth, and log of liquid assets) was dichotomous or continuous with savings dosage as the independent variable (Guo & Fraser, 2010). Those with no account were the reference group. Results from simple logistic regressions and OLS regressions are reported in Table 3. Information is reported before and after weighting using unadjusted and adjusted models.

In stage four, we used logistic regression as the primary analytic tool to assess statistical significance for the overall relationship between each dose separately and the outcome variable with and without propensity score weights. Children with no savings are the main comparison group, and we provide measures of predictive accuracy through the McFadden's pseudo R^2 (not equivalent to the variance explained in multiple regression model, but closer to 1 is also positive). We also report odds ratios (OR) for easier interpretation. The odds ratio is a measure of effect size, describing the strength of association.

Because so few LMI children in our sample graduated college (52), we estimate a model using rare event logistic regression. Research has shown that simple logistic regression can underestimate the probability of rare events (King & Zeng, 2001), and rare event logistic regression corrected for this bias, providing more reliable estimates (King & Zeng, 2001). We used the relogit command in STATA to run the rare event analysis (Tomz, King, & Zeng, 2003).

Results

In this section, we discuss characteristics of LMI and HI children, findings from the covariate balance checks, and logistic regression results by income level for college enrollment and college graduation. Because of selection effects in observational data, propensity score analysis is a more rigorous statistical strategy for estimating effects than a conventional regression or regression-type model. For this reason, only findings from propensity score adjusted models are discussed (Berk, 2004).

Descriptive results on LMI and HI samples

Table 1 provides descriptive statistics for demographic, economic, social, human capital, and asset characteristics of the LMI and HI samples. Overall, children who live in LMI households are more likely to be Black (63%) and live in households whose heads have a high school diploma or less (72%). In contrast, 76% of HI children are White, and 70% of HI household heads have completed at least some college coursework. Moreover, only 46% of LMI children—contrasted with 92% of HI children—live in households in which the head is married. Regarding academic achievement (a combination of math and reading scores), LMI children show lower test scores than their HI counterparts (193 vs. 218). Regardless of income level, the average household size is four, and the average age is 16 in 2002. A large percentage of both income groups (56% of LMI; 33% of HI) live in the North Central region of the country.

HI households hold more in net worth and liquid assets than LMI households, and LMI children are far less likely to have savings than HI children. Only 27% of HI children do not have savings

accounts contrasted with 61% of LMI children. HI children also are more likely to save larger amounts of money for school. For example, only 8% of LMI children have savings for school of $500 or more contrasted with 20% of HI children.

Table 1. Descriptive statistics by income level

Categorical variables	Low- and moderate-income (*N* = 512)		High-income (*N* = 345)	
	Number	Percentage	Number	Percentage
Black	322	63	82	24
Female	190	37	187	54
Head of household is married	236	46	317	92
Region of the country in 2003				
Northeast	50	10	72	21
West	128	25	100	29
North Central	285	56	112	33
South	49	10	61	18
Head of household's education level				
High school or less	367	72	105	30
Some college	104	20	94	27
Four-year degree or more	41	8	146	42
Child's savings dosages				
No account	315	62	92	27
Only basic savings	71	14	81	24
School savings of less than $1	38	7	62	18
School savings from$1 to $499	49	10	41	12
School savings of $500 or more	39	8	69	20
College enrollment	264	52	311	90
College graduation	52	10	123	36
Continuous variables	Mean (median)	SD	Mean (median)	SD
Child's age (2002)	16.06 (15.99)	1.55	16.17 (16.26)	1.46
Academic achievement	193.33 (190.01)	27.16	218.12 (215)	31.55
Parents' education level	12.17 (12.00)	1.99	14.30 (14.00)	2.00
Family size	3.96 (4.00)	1.46	3.97 (4.00)	1.00
Log of family income	7.86 (10.04)	4.28	11.29 (11.22)	0.44
IHS net worth	5.16 (9.85)	8.06	12.00 (12.35)	3.01
Log of liquid assets	3.74 (4.37)	3.43	8.21 (8.43)	2.02

Note. Data from the PSID and its supplements are used. Data imputed using the chained regression method. Weighted data are weighted using 2009 TA supplement weight.

Descriptive results on enrollment and graduation by income level

Overall, children in higher income households are more likely to enroll in college than their LMI counterparts. In the sample of LMI children, fewer Black children (49%) enroll in college than White children (56%). Among female children, 58% enroll in college contrasted with 47% of male children. Similarly, fewer children (46%) in households whose heads have high school diplomas enroll in college than children whose heads have four-year degrees (81%). While 57% of children whose parents are married enroll in college, 47% of children in households in which the head is not married do so. In addition, LMI children in the South region (72%) show higher college enrollment rates than children in other regions. Similarly, among HI children, White children, female children, children from more highly educated, and children in households whose heads are married are more likely to enroll in college (Table 2).

Table 2. College enrollment and graduation by demographic characteristics and saving dosage for high-income and low- and moderate-income children

	College enrollment		College graduation	
	High-income (*N* = 345)	Low- and moderate-income (*N* = 512)	High-income (*N* = 345)	Low- and moderate-income (*N* = 512)
	Percentage	Percentage	Percentage	Percentage
Black	82	49	27	8
White	93	56	38	14
Female	93	58	42	12
Male	87	45	29	08
Head of household is married	91	57	36	11
Head of household is not married	79	47	32	9
Region of the country in 2003				
Northeast	93	48	47	6
West	91	47	31	9
North central	87	51	35	9
South	92	71	31	20
Head's education level				
High school or less	84	46	31	8
Some college	89	62	36	13
Four-year college degree or more	95	81	39	24
Child's savings dosages				
No account	84	45	27	5
Only basic savings	90	49	38	9
School savings of less than $1	95	71	29	13
School savings from $1 to $499	90	65	34	25
School savings of $500 or more	94	72	51	33

Note. Data from the PSID and its supplements are used. Data imputed using the chained regression method.

Table 2 shows that patterns of race and gender disparities in college enrollment exist for college graduation. In the sample of LMI children, White children (14%), female children (12%), children in the most educated households (24%), and children living in the South region (20%) are more likely to graduate from college. The pattern for HI children is similar.

Assets appear to matter for college enrollment and graduation regardless of income level. Among LMI children, 45% with no account, 49% with only basic savings, 71% with school savings of less than $1, 65% with school savings of $1 to $499, and 72% with school savings of $500 or more *enroll* in college. Among the same children, 5% with no account, 9% with only basic savings, 13% with school savings of less than $1, 25% with school savings of $1 to $499, and 33% with school savings of $500 or more *graduate* from college. Even though the overall college enrollment and graduation rates of HI children are higher than those of LMI children, the patterns associated with savings dosages are comparable.

Bivariate results from covariate balance checks

Results from balance checks are presented in Table 3. In the unadjusted sample, almost all covariates show significant group differences regardless of the dosage and income level. After propensity score weighting, group differences are no longer significant in all cases, which suggests that weighting was successful in reducing bias among observed covariates.

For each one-point increase in IHS net worth, children are approximately 16% more likely to enroll in college (OR = 1.155, $p < .01$). Among variables of interest, HI children with school savings of less than $1 are about four times more likely to enroll in college than HI children with no savings account (OR = 3.926, $p < .10$).

Table 3. Covariate balance of dosages of children's savings (no account, basic savings only, school savings of less than $1, school savings of $1 to $499, and school savings of $500 or more) after adjusting for propensity score weight by income level

	No account/Only basic savings				No account/Account with less than $1				No account/Account with $1 to $499				No account/Account with $500 or more			
	Before weighting		After weighting		Before weighting		After weighting		Before weighting		After weighting		Before weighting		After weighting	
	Low- and moderate-income (N = 512)															
	B	*S.E.*	*B*	*S.E.*	*B*	*S.E.*	*B*	*S.E.*	*B*	*S.E.*	*B*	*S.E.*	*B*	*S.E.*	*B*	*S.E.*
Child's age in 2002	0.364*	0.203	0.187	0.237	-0.554**	0.265	0.411	0.395	0.369	0.237	-0.183	0.395	0.343	0.262	-0.077	0.291
Black	-1.260****	0.271	-0.022	0.297	-0.948***	0.348	0.114	0.508	-0.988***	0.312	0.349	0.520	-0.690**	0.346	0.347	0.414
Child is female	0.009	0.263	-0.238	0.309	0.754**	0.367	-0.460	0.545	0.438	0.314	-0.504	0.556	0.239	0.342	-0.334	0.451
Academic achievement	5.513	3.474	3.351	4.647	13.571**	4.541	0.979	5.122	15.007****	4.061	0.453	3.754	18.410****	4.488	-6.354	8.936
Head of household is married	0.368	0.263	0.002	0.310	0.445	0.344	-0.027	0.555	0.545**	0.309	0.405	0.569	0.598**	0.343	-0.330	0.420
Head of household's education 2003	0.784****	0.244	0.258	0.293	0.935****	0.314	0.125	0.648	0.807***	0.284	0.070	0.273	0.751**	0.309	0.220	0.417
Family size in 2003	-0.375	0.232	-0.022	0.257	-0.048	0.305	-0.396	0.390	-0.779***	0.283	0.184	0.544	-0.244	0.304	-0.480	0.502
Region	-0.273***	0.102	-0.070	0.097	-0.066	0.134	0.150	0.129	-0.234*	0.120	0.367	0.282	-0.108	0.132	-0.061	0.166
Log of family income	0.662	0.560	0.107	0.669	-0.348	0.732	0.429	0.740	1.677*	0.654	-1.645	1.794	-0.509	0.723	-0.104	0.826
IHS net worth	2.812***	1.052	0.688	1.319	1.731	1.376	1.830	1.151	2.425**	1.230	-2.119	2.740	0.631	1.360	-2.586	2.611
Log of liquid assets	1.942****	0.437	0.255	0.562	1.649***	0.571	0.215	0.686	2.015****	0.511	-0.720	0.942	1.540***	0.565	0.756	0.573
	High-income (N=345)															
Child's age in 2002	0.245	0.223	0.223	0.253	-0.186	0.240	0.292	0.287	0.013	0.275	0.163	0.368	0.251	0.233	0.191	0.262
Black	-1.773****	0.412	-0.350	0.441	-1.342***	0.405	-0.213	0.455	-0.350	0.391	0.106	0.579	-1.468****	0.402	0.207	0.466
Child is female	0.112	0.305	-0.005	0.343	0.756*	0.340	-0.163	0.395	0.637*	0.386	-0.289	0.469	0.116	0.319	0.303	0.376
Academic achievement	18.643****	4.678	0.764	5.551	15.221***	5.045	4.161	6.074	17.508***	5.765	-1.590	6.507	19.130****	4.890	-0.838	5.502
Head of household is married	0.736	0.621	-0.135	0.676	0.212	0.584	0.016	0.638	-0.248	0.592	-0.103	0.705	0.328	0.582	0.511	0.646
Head of household's education 2003	0.533*	0.273	0.155	0.298	0.057	0.293	0.033	0.380	0.023	0.341	0.268	0.417	0.831***	0.281	-0.010	0.329
Family size in 2003	-0.243	0.282	-0.081	0.312	0.223	0.302	-0.172	0.384	-0.388	0.347	0.195	0.583	0.260	0.294	-0.019	0.276
Region	-0.024	0.155	0.106	0.178	-0.021	0.167	0.160	0.226	0.056	0.191	0.156	0.209	0.080	0.162	0.087	0.186
Log of family income	0.068	0.067	0.030	0.072	0.116	0.072	0.002	0.077	-0.109	0.082	-0.002	0.077	0.117*	0.070	0.046	0.078
IHS net worth	0.946**	0.452	0.670	0.422	0.204	0.487	0.234	0.591	-0.642	0.557	0.540	0.632	1.198**	0.472	0.721	0.438
Log of liquid assets	0.969***	0.303	0.365	0.273	0.782**	0.326	-0.073	0.523	0.587	0.373	0.130	0.281	1.125****	0.316	-0.129	0.597

Note. Weighted data from the PSID and its supplements are used. Data imputed using the chained regression method. To conserve space, we present imbalance checks using the reference only: no accounts. This is the comparison of most interest in this study. The weights (adjusted) are based on the propensity scores (or predicted probabilities) calculated using the results of the multinomial logit model. Comparison groups consist of all children not in the dose category. Estimates are propensity score-adjusted using the weighting scheme in Guo & Fraser, 2010 (see also Foster, 2003 and Imbens, 2000). The propensity score weights are based on the propensity scores (or predicted probabilities) calculated using the results of the multinomial logit model. *p < .10; **p < .05; ***p < .01; ****p < .001.

Logit results with no savings as reference group – college enrollment by income level

Table 4 provides unadjusted and adjusted logit models examining the relationships among different dosages of children's savings and college enrollment by income level. In the adjusted model for LMI samples, statistically significant covariates that are predictors of college enrollment are the child's age, race, gender, academic achievement, and region of the country lived in; the head household's marital status; log of family income; and IHS net worth. Controlling for all other variables, for each one-year increase in age, children are about 27% more likely to enroll in college (OR = 1.273, $p < .05$). Black children are more than twice as likely to enroll in college than White children (OR = 2.132, $p < .10$). Female children are about 88% more likely to enroll in college than male children (OR = 1.875, $p < .05$). For each one-point increase in academic achievement score, children are approximately 5% more likely to ever enroll in college (OR = 1.047, $p < .001$). Children whose heads of household are married are about three and a half times more likely to enroll in college than children whose heads of household are not married (OR = 3.616, $p < .001$). Children in the South region are about seven times more likely to ever enroll in college than children in the Northeast (OR = 6.986, $p < .01$). For each one-point increase in family income, children are 20% less likely to enroll in college (OR = .802, $p < .01$). In contrast, for each one-point increase in IHS net worth, children are approximately 13% more likely to ever enroll in college (OR = 1.131, $p < .001$).

Regarding school savings dosages, only having school savings from $1 to $499 is a statistically significant predictor of college enrollment in the adjusted model for the LMI sample. LMI children with school savings of $1 to $499 before reaching college age are more than three times more likely to enroll in college than children with no savings account (OR = 3.321, $p < .05$). In the sample of HI children, academic achievement, IHS net worth, and having school savings of less than $1 are statistically significant predictors of college enrollment. For each one-point increase in academic achievement scores, a child is about 3% more likely to enroll in college when all other variables are controlled for (OR = 1.030, $p < .001$).

Table 4. Logit examining the relationship between children's savings and college enrollment by income level

	Low- and moderate-income (*N* = 512)						High-income (*N* = 345)					
	Logit – unadjusted			Logit – PSW adjusted			Logit – unadjusted			Logit – PSW adjusted		
	B	*S.E.*	*O.R.*	*B*	*S.E.*	*O.R.*	*B*	*S.E.*	*O.R.*	*B*	*S.E.*	*O.R.*
Child's age in 2002	0.050	0.068	—	0.241**	0.111	1.273	0.008	0.156	—	-0.060	0.185	—
Black	0.671 **	0.272	1.956	0.757*	0.393	2.132	0.197	0.557	—	0.729	0.620	—
Child is female	0.550 ***	0.204	1.733	0.629**	0.320	1.875	0.904**	0.403	2.469	0.088	0.446	—
Academic achievement	0.039 *	0.005	1.040	0.046****	0.008	1.047	0.033****	0.009	1.034	0.029****	0.008	1.030
Head of household is married	0.395 ***	0.229	1.485	1.285****	0.368	3.616	0.640	0.636	—	0.026	0.781	—
Head household's education level in 2003	0.205	0.060	—	0.169	0.103	—	0.239**	0.110	1.270	0.250	0.138	—
Family size in 2003	0.031	0.074	—	-0.089	0.138	—	0.248	0.299	1.282	0.376	0.272	—
Region of the country in 2003 (Northeast as reference)												
West	-0.097	0.409	—	0.234	0.602	—	0.110	0.609	—	0.295	0.698	—
North central	0.110	0.381	—	0.285	0.557	—	-0.264	0.556	—	-0.525	0.633	—
South	1.038	0.507	—	1.944***	0.699	6.986	0.299	0.715	—	0.134	0.804	—
Log of family income	-0.063 **	0.042	0.939	-0.220***	0.071	0.802	0.175***	0.943	1.191	0.694	1.248	—
IHS net worth	0.030	0.022	—	0.124***	0.040	1.131	0.127	0.044	—	0.144***	0.044	1.155
Log of liquid assets	-0.027	0.046	—	-0.067	0.069	—	-0.048	0.112	—	0.154	0.108	—
Child's savings dosage												
No account (reference)	—	—	—	—	—	—	—	—	—			
Only basic savings	0.013	0.303	—	-0.278	0.349	—	-0.303	0.555	—	-0.322	0.631	—
School savings of less than $1	0.629	0.400	—	0.469	0.437	—	0.989	0.659	—	1.368*	0.750	3.926
School savings from $1 to $499	0.531 *	0.402	1.701	1.200**	0.518	3.321	-0.065	0.654	—	0.179	0.724	—
School savings of $500 or more	0.755 ****	0.421	2.127	0.386	0.457	—	0.062	0.691	—	-0.401	0.581	—
	P*seudo* R^2 = 0.189			P*seudo* R^2 = 0.339			P*seudo* R^2 = 0.210			P*seudo* R^2 = 0.225		

Note. Weighted data from the PSID and its supplements are used. Data imputed using the chained regression method. S.E. = robust standard error. O.R. = odds ratios. For the adjusted model, estimates are propensity score-adjusted using the weighting scheme in Guo & Fraser, 2010 (see also Foster, 2003 and Imbens, 2000). The propensity score weights are based on the propensity scores (or predicted probabilities) calculated using the results of the multinomial logit model.
*p<.10; **p<.05; ***p<.01; ****p<.001.

Logit results with (no savings as reference group) – college graduation by income level

Table 5 provides information on the unadjusted, adjusted, and rare event logit models examining the relationships among different dosages of children's savings and college graduation among the LMI sample. In the rare event logit model for the LMI sample, statistically significant controls that are predictors of college graduation are child's age and academic achievement, log of family income, and IHS net worth. For each one-year increase in age, children are about 35% more likely to graduate from college (OR = 1.352, $p < .01$).

Among variables of interest, children with school savings of $1 to $499 are more than four and half times more likely to graduate from college than children with no savings account (OR = 4.471, $p < .01$). In addition, LMI children with school savings of $500 or more are about five times more likely to graduate from college than LMI children with no savings account (OR = 4.949, $p < .01$).

For each one-point increase in academic achievement score, children are approximately 2% more likely to graduate from college (OR = 1.015, $p < .05$). For each one-point increase in family income, children are 20% less likely to graduate from college (OR = 0.803, $p < .10$) when controlling for all other factors. Conversely, for each one-point increase in IHS net worth, children are approximately 11% more likely to graduate from college (OR = 1.114, $p < .10$).

Table 6 provides information on college graduation rates among the sample of HI children. Controls that are statistically significant predictors of college graduation are child's age, gender, academic achievement, and region of the country lived in; log of family income; and log of liquid assets. For each one-year increase in age, children are about two and a half times more likely to graduate from college (OR = 2.542, $p < .001$). Female children are about three times more likely to graduate from college (OR = 2.912, $p < .01$). For each one-point increase in academic achievement score, children are approximately 2% more likely to graduate from college (OR = 1.022, $p < .01$). Children who live in the West region are about 54% less likely to graduate from college than children who live in the Northeast (OR = 0.464, $p < .10$). When controlling for all other factors, for each one-log point increase in family income, children are more than twice as likely to graduate from college (OR = 2.176, $p < .10$). For each one-point increase in log of liquid assets, children are approximately 30% more likely to graduate from college (OR = 1.299, $p < .01$).

Among variables of interest, children with school savings of less than $1 are about 60% less likely to graduate from college than children with no savings (OR = 0.415, $p < .10$). Furthermore, HI children with school savings of $500 or more are 52% more likely to graduate from college than HI children with no savings (OR = 1.520, $p < .001$).

Table 5. Logit examining the relationship between children's savings and college graduation for low- and moderate-income children

	Low- and moderate-income (*N* = 512)								
	Logit – unadjusted			Logit – PSW adjusted			Rare event logit – PSW adjusted		
	B	*S.E.*	*O.R.*	*B*	*S.E.*	*O.R.*	*B*	*S.E.*	*O.R.*
Child's age in 2002	0.329***	0.109	1.390	0.304*	0.158	1.355	0.302 ***	0.105	1.352
Black	-0.062	0.441	—	-0.680	0.573	—	-0.060	0.417	—
Child is female	0.300	0.339	—	0.738	0.453	—	0.259	0.333	—
Academic achievement	0.016**	0.006	1.016	0.020*	0.011	1.020	0.015 **	0.006	1.015
Head is married	-0.089	0.341	—	-0.342	0.459	—	-0.081	0.329	—
Head's education level in 2003	0.137	0.107	—	0.015	0.154	—	0.128	0.103	—
Family size in 2003	0.085	0.137	—	0.110	0.153	—	0.084	0.134	—
Region of the country in 2003 (Northeast as reference)									
West	0.608	0.810	—	0.947	0.959	—	0.459	0.767	—
North Central	0.736	0.801	—	1.239	0.953	—	0.577	0.768	—
South	1.354	0.855	—	1.490	1.075	—	1.172	0.820	—
Log of family income	-0.320***	0.121	0.726	-0.504	0.331	—	-0.219 *	0.116	0.803
IHS net worth	0.169***	0.061	1.184	0.271	0.187	—	0.108 *	0.589	1.114
Log of liquid assets	0.025	0.081	—	0.042	0.092	—	0.027	0.079	—
Child's savings dosage									
No account (Reference group)							—	—	—
Only basic savings	0.195	0.564	—	0.526	0.551	—	0.237	0.539	—
School savings of less than $1	0.550	0.610	—	-0.196**	0.666	0.822	0.592	0.589	—
School savings from $1 to $499	1.571***	0.505	4.810	1.420***	0.605	4.137	1.498 ***	0.486	4.471
School savings of $500 or more	1.697***	0.506	5.458	1.508**	0.533	4.519	1.599 ***	0.464	4.949
	P*seudo* R^2 = 0.218			P*seudo* R^2 = 0.228					

Note. Weighted data from the PSID and its supplements are used. Data imputed using the chained regression method. S.E. = robust standard error. O.R. = odds ratios. For the adjusted model, estimates are propensity score-adjusted using the weighting scheme in Guo & Fraser, 2010 (see also Foster, 2003 and Imbens, 2000). The propensity score weights are based on the propensity scores (or predicted probabilities) calculated using the results of the multinomial logit model. Rare event analysis is used due to the small number of low- and moderate-income children who graduate college (King & Zeng, 2001). *p < .10; **p < .05; ***p < .01; ****p < .001.

Table 6. Logit examining the relationship between children's savings and college graduation for high-income children

	High-income (N=345)					
	Logit - unadjusted			Logit – PSW adjusted		
	B	*S.E.*	*O.R.*	*B*	*S.E.*	*O.R.*
Child's age in 2002	0.819****	0.124	2.268	0.933****	0.144	2.542
Black	-0.175	0.418	—	-0.258	0.475	—
Child is female	1.064***	0.306	2.897	1.069***	0.336	2.912
Academic achievement	0.022***	0.006	1.022	0.022***	0.007	1.022
Head of household is married	-0.041	0.656	—	-0.049	0.668	—
Head of household's education level in 2003	-0.090	0.081	—	-0.139	0.091	—
Family size in 2003	0.113	0.149	—	0.045	0.180	—
Region of the country in 2003 (Northeast as reference)						
West	-0.621	0.391	—	-0.767*	0.447	0.464
North central	-0.181	0.418	—	-0.498	0.473	—
South	-0.463	0.463	—	-0.708	0.514	—
Log of family income	0.691**	0.332	1.996	0.777*	0.408	2.176
IHS net worth	0.139**	0.055	1.150	0.083	0.055	—
Log of liquid assets	0.080	0.072	—	0.261***	0.096	1.299
Child's savings dosage						
No account (reference)						
Only basic savings	-0.260	0.448	—	-0.466	0.515	—
School savings of less than $1	-0.405	0.448	—	-0.880*	0.515	0.415
School savings from $1 to $499	0.011	0.479	—	-0.316	0.539	—
School savings of$500 or more	0.534****	0.396	1.706	0.419****	0.452	1.520
	P*seudo* R^2 = 0.266			P*seudo* R^2 = 0.309		

Note. Weighted data from the PSID and its supplements are used. Data imputed using the chained regression method. S.E. = robust standard error. O.R. = odds ratios. For the adjusted model, estimates are propensity score-adjusted using the weighting scheme in Guo & Fraser, 2010 (see also Foster, 2003 and Imbens, 2000). The propensity score weights are based on the propensity scores (or predicted probabilities) calculated using the results of the multinomial logit model.
*p < .10; **p < .05; ***p < .01; ****p < .001.

Discussion

In this paper, we posit that children's savings have the potential to create positive psychological effects in addition to direct financial benefits. Nowhere might evidence of this be clearer than for children who have designated small amounts of savings for school. Money in school savings accounts likely will not make a meaningful difference in actual ability to pay for college, but the psychological effects may be beneficial. In this study, we examine whether designating small amounts of money for school has a positive effect on whether LMI and HI children enroll in and graduate from college.

We find that designating small amounts of money for school ($1 to $499 for LMI children and less than $1 for HI children) can increase the odds that both groups of children ever enroll in college. This contrasts findings in Elliott, Constance-Huggins, and Song (2012) that HI children's school savings amounts are not significant predictors of their college progress. This might be because the authors measure school savings as a dichotomous variable (having no or only basic savings as the reference group and having savings for school as the treatment group). They also examine college progress (i.e., being currently enrolled in or having already graduated from college), whereas we measure whether a child ever attended college. Further, we use propensity score weighting. In our non-weighted HI sample, we find that school savings at any dosage is not a significant predictor of enrollment, which is similar to findings in Elliott et al. (2012). While having savings of less than $1 is statistically significant, it is significant at $p<.10$. Despite these differences, it does raise some doubt about whether or not designating savings for school might has positive effects for HI and LMI children regarding college enrollment and graduation. However, it does not mean that having school savings might not have other types of positive effects like encouraging savings throughout adulthood (Elliott, Rifenbark, Webley, Friedline, & Nam, 2012).

Several findings among the control variables are of particular interest. Family income is a negative predictor of ever enrolling in college among LMI children but a positive predictor among HI children. This might help explain findings by (2012) and Friedline, Elliott, and Nam (2012) that income is a negative predictor of college enrollment using a full sample and a sample separated by race (Black/White), respectively. Negative findings for LMI and positive findings for HI samples suggest that LMI children may be influencing findings in Elliott (2012a) and Friedline, Elliott, and Nam (2012) by negating one another.

How do we understand the two findings on income in this study? As household income increases (closer to $50,000), it may become more difficult for children to acquire financial aid. For example, Elliott and Friedline (2012) find that moderate-income children are more likely to report paying for college with their own contributions than low-income children and are less likely to report using societal resources (i.e., scholarships) than low-income children. That is, more financial aid might be available for low-income children. Couple this with the fact that moderate-income families have less of their own income to contribute to college expenses than HI families. While income reduces the odds that LMI children enroll in college, family net worth increases the odds, which suggests that family net worth acts as a protective factor for LMI children. Therefore, having assets might be particularly important for LMI children (also see Elliott, 2013).

Regarding college graduation, having some amount of money for school appears to matter, but having even small amounts (i.e., $1 to $499) improves the odds that LMI children will graduate.

Even though designating school savings of less than $1 is not statistically significant in the weighted rare event model, it is significant in the weighted logit model. Moreover, it reduces the odds in the logit model that LMI children graduate. Although the weighted logit findings are less reliable given the small number of LMI children who have graduated from college, these findings reinforce a potentially important reality or caution. Although having even less than $1 in savings increases the odds that LMI children will enroll in college, persistence in and graduation from college also might involve being able to pay school expenses with savings. That is, the psychological effects of having savings are not enough to guarantee persistence and graduation. Psychological effects and actual savings amounts play important roles in influencing children's college outcomes.

The HI model is equally informative. For HI children, designating school savings of $500 or more improves their odds of graduating from college, while designating school savings of less than $1 decreases them. We suggest that these effects result from the process of designating savings for college costs. The degree to which designating savings for school is a predictor of college graduation might depend on the degree to which children perceive college costs as a barrier to attending, persisting in, and completing college. Because HI children may have fewer doubts about their abilities to attend and pay for college, school savings may make less of a difference in college outcomes when amounts are not high.

HI children might benefit from an environment that consistently suggests to them that their parents will be able to finance college. This theme is apparent in research that examines children's expectations about attending and graduating from college. While many LMI children expect to graduate from college, almost all HI children expect to do the same (e.g., Elliott et al., 2012). Further, HI children are far less likely to be concerned about whether they will be able to pay for college (Hahn & Price, 2008). Having savings for school may not have the same psychological effects for HI children as LMI children if they are unable to derive tangible benefits (e.g., take money out to buy books or pay tuition). Regarding college enrollment, HI children do seem to benefit psychologically from having school savings of less than $1. Also, some evidence suggests that savings of less than $1 can have a negative effect on college graduation outcomes for LMI children in the PSW adjusted model but not in the rare event model (see Table 5). Clearly, more research is needed to investigate how children's savings may affect income groups differently.

Limitations

The results of this study should be considered along with several limitations, including that only 10% of children in the LMI sample graduated from college, making the ability to estimate this college outcome with traditional logistic regression methods questionable. In some cases, traditional logistic regression has been found to underestimate the probability of rare events (King & Zeng, 2001). To remedy this limitation, we also used rare event logistic regression that corrects for this bias and provides more reliable estimates of LMI children's college graduation rates.

Another limitation is the use of propensity score weighting. Propensity score weighting may increase random error in the estimates due to endogeneity and specification of the propensity score estimation equation (Freedman & Berk, 2008). In some cases, propensity score weighting has been found to exaggerate endogeneity (Freedman & Berk, 2008). Children's savings may be endogenous if assignment into the multi-treatment/dosage groups correlates with unobserved covariates that impact their college enrollment and graduation. Endogeneity may be introduced due to unknowingly

omitting relevant or important covariates from this study. Concerns regarding endogeneity can be somewhat mitigated, however, given the growing number of studies that explore the children's savings–college education relationship and provide researchers with information about relevant covariates to include. In this study, we include family economic resources (e.g., income, net worth, and liquid assets) because they have been found to relate consistently to children's college outcomes much more than traditional covariates (e.g., gender, race, and academic achievement) (Elliott et al., 2011; Elliott & Friedline, 2012).

Finally, there are limitations regarding the measurement of the children's savings variable. First, a majority of LMI children do not have savings accounts (62%), which resulted in small cell sizes (14% had only basic savings, 7% had school savings of less than $1, 10% had school savings of $1 to $499, and 8% had school savings of $500 or more). While the numbers within each cell were sufficient to conduct our analyses, caution in interpretation is warranted. Second, the ideal would be to compare more sensitive thresholds of savings amounts and their relationships with college outcomes. However, children saved relatively small amounts in 2002, and cell sizes become negligible when savings amounts are divided into smaller, more sensitive categories. To address this issue we created two amounts: school savings of $1 to $499 and school savings of $500 or more. This allowed us sufficient sample sizes within cells to examine children's savings amounts.

Policy implications

Findings from this study appear to show that designating even very little savings for school can have a positive effect on LMI children's enrollment in college, which suggests that simply providing children with accounts could have positive effects. Further, findings suggest that having even a small amount of school savings (e.g., $1 to $499) can have positive effects on LMI children's persistence through graduation. Results from this study also suggest that children's savings programs can have positive effects on HI children's enrollment and graduation rates when they have larger amounts of money in the accounts.

Findings also suggest that policies to help children develop mental accounting (the process of dividing current and future money into different categories to monitor spending [Thaler, 1985]) related to school might improve children's college outcomes more effectively than policies that create general savings accounts alone (for additional information on the relationship between the small-dollar accounts examined in this study and mental accounting see Elliott, 2012a). In discussing how this might happen, Elliott (2012a) states:

> I suggest that the mental accounting categorization process (i.e., designating savings for school) helps children manifest abstract conceptions of the self (e.g., college-bound). According to the principles of [Identity-Based Motivation] IBM—identity salience, congruence with group identity, and interpretation of difficulty—mentally designating savings for college, regardless of the amount, indicates that college is the child's goal and expectation and the child sees saving as a relevant behavioral strategy for overcoming the difficulty of paying for college. (p. 9)

So, we suggest that it might be important to teach children about the value of designating some savings for educational purposes, which could be done in financial education classes usually included in CDA programs.

Conclusion

Our findings suggest that designating less than $1 for school is a much more positive and powerful predictor of college enrollment than college graduation. The effects of school savings on enrollment may be based not only on what children can purchase at the moment but also on the cumulative psychological effects of having savings. That is, psychological effects of having savings on engagement and children's academic achievement in early life result in their being better academically prepared for the rigors of college (Elliott, 2009; Elliott, Jung, & Friedline, 2010).

However, having slightly higher but still very small amounts (e.g., $1 to $499) may be important for improving graduation outcomes among LMI students. This makes sense based on the theoretical framework laid out by Elliott (2012a) and adopted in this paper. Elliott suggests that having a small-dollar account might signal to a child that financing college is possible and could mean that the child is considering future expected savings rather than current savings. However, it is less realistic to expect to save money for school once they are in college. Therefore, a part of the effect of school savings on persistence might have to do with children having some savings on hand to pay for college expenses.

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