THE INFLUENCE OF EARLY INFORMATION ON POSTSECONDARY AFFORDABILITY

BY

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DISSERTATION

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ABSTRACT

Misconceptions on affordability remain a barrier to postsecondary access for millions of potential students. When students recognize financial aid availability during secondary school years, they gain the capability to better establish a curricular path that aligns with postsecondary aspirations. This dissertation assesses the use of residency-based financial aid programs and parents' college assets as methods to generate early information on postsecondary affordability. Following a three-paper format, the first paper develops a typology organizing the growing number of residency-based "Promise" programs around the country. The typology captures variations in the geographic scope for eligibility, supplementary qualifications, funding sources, value, and redeeming criteria to generate a description and list of comparable programs. Identifying program comparability is a necessary step for research examining program outcomes. The first paper uses a cluster analysis methodology to identify programs comparable based on the advertised operational characteristics. I find three distinctly different groups of residency-based financial aid programs, which I term state-based aid programs, institutionally funded programs, and community-sustained programs. The typology is extended to identify the specific operational characteristics for which residency-based, community-sustained financial aid programs differ. The second paper uses a unique institutional-level dataset and quasi-experimental Difference-in-Difference design to examine changes in college readiness, postsecondary outcomes, and curriculum decisions resulting from the residency-based, community-sustained Dell and Evelyn Carroll Scholarship. The award guarantees all Meridian High School students last-dollar funding for unmet need at Richland Community College. I find that information about Carroll Scholarship eligibility increases the college-readiness levels among high-achieving high school graduates who elect to enroll at Richland. After enrollment, all Carroll-eligible students register for, and earn, a statistically significant increased number of credit hours. I also find evidence that the Carroll Scholarship impacts student's curriculum selection. The final paper uses a quantitative, quasi-experimental design of the nationally representative Education Longitudinal Study of 2002. Propensity Score Matching models are used to estimate different parents' college asset savings strategies impacts the likelihood of a child enrolling in postsecondary education after completing high school. I find an enrollment association from parent's postsecondary savings across different socioeconomic and sociodemographic groups. The models evaluate student responsiveness differences based on socioeconomics, race, and ethnicity, and control for secondary school academic achievement and the amount saved.

Keywords: higher education; financial aid; Promise programs; place-based aid; universal eligibility; parent college assets; postsecondary savings; quasi-experimental design; propensity score matching; difference-in-difference

To my late Father, William, and Mother, Wendy

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Paper One: A Typology of Residency-Based Financial Aid Programs

Sparked by the announcement of the Kalamazoo Promise in 2005, an increasing number of communities have established financial aid programs aimed at providing postsecondary access to all students residing within a specified geographic boundary. The programs *typically* award aid without an individual selection process or considering student characteristics, such as financial need or academic merit. Instead, the promise of financial aid is based on residency requirements easily interpreted by students and their family, such as longevity within the school district. This format for financial aid has drawn a number of different monikers among researchers, most commonly, Promise programs, place-based aid, universally eligible, and early commitment programs (Andrews, 2013; Blanco, 2009; Daun-Barnett, 2011; Miller-Adams, 2015; Schwartz, 2008). Prior literature on residency-based aid programs have not addressed questions regarding program comparability; for instance, whether state-based programs and institutional aid should be used as a comparative measure for outcomes. This typology makes a unique contribution to the literature by examining a list of financial aid programs and applying multiple cluster analysis methodologies to identify which programs are sufficiently similar for comparative purposes.

Residency-based aid programs can help students navigate information barriers associated with estimating higher education's cost of attendance (Ash & Ritter, 2014; Bartik, Hershbein, & Lachowska, 2015; Carruthers & Fox, 2016; Hershbein, 2013; Penn, 2012). Incomplete and inaccurate information on postsecondary affordability is a substantial barrier to postsecondary access for millions of potential college students (Heller; 2006; Perna, 2006; Kelchen & Goldrick-Rab, 2013). The close proximity of a local residency-based aid program creates a clear and direct network for students to receive personalized information on eligibility. When a student is able to continuously reassess their estimated aid award, using the program's transparent eligibility criterion, students receive information on postsecondary affordability in advance of the normal financial aid process, the Free Application for Federal Student Aid (FAFSA). Providing early awareness of postsecondary affordability is credited with prompting students to make college-going decisions earlier in high school, improving students' efforts toward academic performance, and broadening students' postsecondary institutional choice, to name a few immediate effects (Ash & Ritter, 2014; Bartik, Hershbein, & Lachowska, 2015; Carruthers & Fox, 2016; Hershbein, 2013; Penn, 2012).

The benefits cited above are drawn from a body of literature that examines the impact of a handful of residency-based financial aid programs. However, as a whole, there has been a lack of research examining the impact of multiple programs from this budding format of financial aid. One reason for the limited amount of research is that a residency stipulation for financial aid is vague and does not address other potential differences among programs. For instance, a program described as residency-based does not speak to how researchers should qualify the geographic range of location, characterize programs with non-residency-based eligibility requirements (for instance, minimum grade point average), categorize programs with different maximum aid amounts, or represent programs that limit the number of redeemable institutions. The individual choices made by researchers to address these comparability questions results in new knowledge on program outcomes, but only within the narrow focus of how the author addressed program comparability. For example, Andrews (2013) compares Georgia's HOPE scholarship and the Kalamazoo Promise based on the relatively equal-sized aid awards, yet the two programs have dissimilar eligibility characteristics. Georgia's program uses a state-based residency requirement and provides 90% tuition coverage to all students who graduate high school with a 3.5 grade point average or above (Long, 2004). Kalamazoo is a locally funded program that provides a varying range of tuition coverage based solely on the number of years a student attended the city's public schools (Miller-Adams, 2015). Comparing the two programs may be appropriate for some research, but fundamentally the programs differ in substantial ways like providing students information on postsecondary affordability.

The typology presented here fills a gap in the literature by examining the distinction among residency-based financial aid programs under a new focus − the connection between residency-based aid programs and providing students information on postsecondary access and affordability. This typology makes two major contributions. First, I use cluster analysis to create multiple groups of residency-based aid programs using the characteristics from each program's individual operating procedures. I define operation procedures as the decisions made by programs, and advertised to students, regarding the process for distributing financial aid. Operating procedures include decisions on how to define residency, to what extent non-residency-based eligibility criteria are used, the process for determining aid awards, and the value of the aid award. The programs included in this research have all begun distributing financial aid prior to the 2016-2017 academic year. The second contribution of this typology is the descriptions it offers of the specific ways programs developed within local communities differ. Cluster analysis is a useful tool for identifying groups of programs comparable overall; however, one limitation of cluster analysis is its inability to distinguish where programs within a group have variation. For this reason, I extend the typology to include a more in-depth examination of the range of program variation among community-sustained programs.

This typology does not intend to organize the existing research on residency-based aid programs; rather, the purpose is to illustrate the similarities and differences among programs that use a residency requirement for financial aid eligibility. The resultant list of comparable programs can be used as the foundation for future research centered on residency-based aid programs and student information on postsecondary access and affordability. Formally, the research question in this study is:

1.) *How can differences in residency-based financial aid programs be categorized to identify meaningful program variability in a typology?*

Next, I give background to the growth of residency-based aid programs, from early examples of residency-based aid programs through current national policy considerations. I include a description of how the expansion of programs fosters characteristics making different typologies necessary. Second, I review prior literature that defines the characteristics present in residency-based aid programs and other typologies that describe program classifications. Then, I describe the method used for acquiring a sample of residency-based aid programs, the dataset I create, and the cluster analysis methodology I use to group programs. Following the cluster analysis description, I detail the descriptive statistics of the groupings that are identified. Lastly, I describe the degree of program variability among community-sustained programs and demonstrate how spectrums provide a tool for researchers to assess comparability among individual programs.

Background

The expansion of residency-based aid programs has been sparked by the success of early examples such as the Kalamazoo Promise (Andrews, 2013). The Kalamazoo Promise is funded through contributions of anonymous donors and provides first-dollar aid award to Kalamazoo Public School (KPS) graduates. Kalamazoo does not use any selectivity metrics to determine eligibility; instead, aid award is determined using only a percentage scale derived from a student’s longevity in the city’s public schools. The award percentage equation is demonstrated in Equation 1.[1] The Kalamazoo Promise will pay 100% of tuition for students who matriculated from kindergarten through high school graduation. Students who enter between 1st and 3rd grades receive 95% tuition coverage, while students who enter later are eligible for 5% less for each year after 3rd grade they enter the school district. Students who enter during, or after, 10th grade are ineligible for any funding. Aid is redeemable at any public two- or four-year institution within the state of Michigan and private institutions at a prorated rate.

$$\textit{Award percentage} = \begin{cases} 100\%,\ if\ grade\ entered = kindergarten \\ 95\%,\ if\ 1st \leq grade\ entered\ \leq 3rd\ grade \\ 95\% - 5\%\ x\ [grade\ entered - 3],\ if\ 3rd < grade\ entered < 10th\ grade \end{cases} \quad (1)$$

Kalamazoo witnessed student input (i.e. effort) increases immediately after the program's announcement. Students exhibited fewer behavior issues, increased enrollment in advanced placement courses, increased college aspirations, and demonstrated broader postsecondary institutional considerations (Andrews, DesJardins & Ranchhod, 2010; Bartik, Hershbein, & Lachowska, 2015; Miller-Adams, 2015). The benefits generated by the program extended beyond the KPS student population. Among the cited social benefits, the parents of KPS students increased their level of social involvement in the school district after the program was implemented, voters approved a bond mileage to fund two new school buildings in the district, commercial property value increased, and local businesses donated resources to establish an after-school tutoring center (Miller-Adams, 2015). The generosity of the program and the number of non-education-related social benefits are among the reasons why scholars, like Andrews (2013), call Kalamazoo the gold standard for place-based programs.

[1] I use percentages in Equation 1 to demonstrate the magnitude of awards. A more accurate method of calculation is to convert the percentages to decimal form (dividing by 100).

The immediate returns observed in Kalamazoo prompted the development of similar programs across Michigan. The state of Michigan enacted tax legislation in 2008 to encourage 10 new Promise Zone programs in low-socioeconomic areas (Miller-Adams, 2015). The Michigan Promise Zone Authority requires that the 10 communities collect the resources necessary to fund all eligible students for the first two years of the program (Miller-Adams, 2015). After the two-year mark, the communities are qualified to receive state education tax appropriations to be used to fund future years (Miller-Adams, 2015).

The national attention received by the Kalamazoo Promise coincides with a swell of new residency-based aid programs across the country. Communities began to develop their own Kalamazoo-type "Promise" programs, frequently using the word "Promise" in the program title. Cities of Promise (2016), an organization that consult on residency-based aid programs, list communities in 36 different states as operating or developing financial aid programs using residency-based eligibility stipulations. The range of locales that are developing programs extends from rural communities, such as Shelby, NC (population: 20,000), to large metropolitan locations, such as Pittsburgh, PA (population: 300,000) (Census Bureau, 2017).

Basing financial aid awards on geographic residency has evolved into the idea of "free college" in a number of states. Oregon and Tennessee have passed state legislation designed to reduce the out-of-pocket cost associated with postsecondary enrollment, modeling their programs after community level programs. Bill Haslam was mayor of Knoxville when the Knoxville Achieves program (later to become tnAchieves) was developed (Fain, 2014). After winning the Governorship, Haslam used the model from Knox Achieves and the Ayers Foundation Scholarship (another local program) as the basis for the statewide Tennessee Promise (Carruthers & Fox, 2016; Fain, 2014). The Tennessee Promise legislation was passed in 2014 and commits to cover the cost of attendance at any of the state's 39 two-year institutions (community colleges or applied technology colleges) for all graduates of Tennessee high schools. Like Tennessee, the Oregon Promise is a statewide program for students enrolling at in-state two-year community colleges. The Oregon Promise has important distinctions. Students must graduate high school with a minimum 2.5 GPA (Oregon Promise, 2017). After one full year in operation, the Oregon Promise opted to make changes to the eligibility requirements. Beginning in Fall 2017, the Oregon Promise will contain a financial need provision where students must meet minimum Expected Family Contribution (EFC) requirements to earn eligibility (Theen, 2017). Arizona, California, Illinois, Kentucky, Maryland, Massachusetts, Minnesota, Mississippi, New York, Oklahoma, Washington, and Wisconsin have proposed legislation for similarly structured statewide financial aid programs (NCSL, 2016).

The idea of a nationwide "free community college" initiative is also linked to residency-based aid and is a point of debate in federal policy (Jesse, 2015; NCSL, 2016; White House, 2015). In 2015, the administration of President Barack Obama began the push for tuition-free community colleges nationwide (White House, 2015). In a speech at Macomb Community College in Detroit, MI, President Obama attributed the growing number of residency-based aid programs as evidence that fiscal access to postsecondary education can create widespread social benefits (Jesse, 2015; White House, 2015). The idea of "free community college" extended into the 2016 presidential campaign trail for a number of candidates. Democratic candidate and Vermont State Senator Bernie Sanders proposed debt-free college education by eliminating tuition costs for all postsecondary institutions (Friends, 2016). Democratic candidate and Former First Lady Hillary Clinton proposed a program to offer states a monetary incentive to create tuition policies that eliminated the need for student loans (Douglas-Gabriel & Gearan, 2015).

As the number of programs that use a residency-based eligibility stipulation expand, research on program outcomes will become increasingly important for questions regarding academic, social, and fiscal benefits; however, not all programs are uniform. The rapid expansion of programs has led to a growing problem of program comparability, particularly as communities adopt unique eligibility stipulations beyond residency. Differences in the operational procedures of programs blur the line of what constitutes residency-based financial aid and programs that elect to award aid to students from within a specified geographic location. Four primary issues have arisen that make characterizing residency-based programs and identifying program comparability difficult for researchers.

First, each residency-base program employs its own unique, limited set of resources to meet the community objective. Scarce resources (for example, available funding or fundraising capabilities) may mean that communities are forced to include additional eligibility qualifications beyond residency to reduce the number of eligible students (Mumper, 2003). Secondary qualifications can include minimum grade point average, maximum income thresholds, and institutional choice stipulations, among other things. The additional program characteristics allow the community to target a specific student demographic and control how many students will be eligible. From a student's vantage point, increasing the number of secondary qualifications reduces the transparency for assessing eligibility. When students perceive uncertainty in earning eligibility, responsiveness can be negatively influenced (Daun-Barnett, 2011; Doyle, 2008).

Second, a large number of programs use residency-based stipulations and the label "Promise" interchangeably; however, the title "Promise" may not equate to a commitment for financial aid. One example is the Rockford (Illinois) Promise. Rockford's program operates as a lottery with a residency-based entrance criterion. Graduating students from any of the five Rockford public high schools become eligible after providing proof of submitting a FAFSA application and completing a Rockford Promise information application (Rockford Cosmopolitan Club, 2015). The award process is determined by a random drawing in the months prior to high school graduation. The lottery system used by Rockford is more akin to a selection process for aid award because eligibility does not guarantee aid. The aid award of one student (whose name is drawn during the lottery) comes at the expense of another student not being awarded aid. Despite being based on residency, the Rockford Promise does not provide students with early information on postsecondary affordability.

Third, financial support and the specified geographic location for the award are only two ways the programs are designed to be community-centric. Program benefits ripple to non-education-based aspects of the local economy. An increasing number of programs cite economic development as the primary objective and financial aid as the incentive. Residency-based financial aid programs are a fiscally efficient method to train the local labor force, because the value of social returns can outweigh local monetary contributions (Andrews, 2013). In addition, the creation of a residency-based aid program is connected to local economic development through increased consumer spending, population migration, and job creation (Bartik, Eberts, & Huang; 2010; Hershbein, 2013; LeGower & Walsh, 2014; Miller-Adams, 2015). Programs with an economic development objective may incorporate a different list of program characteristics relative to programs with the primary objective of financing postsecondary access with ancillary economic benefits. For example, the programs may not actually provide any financial aid dollars but instead provide services for applying for external financial aid. One such example is the 10,000 Degrees Program in San Rafael, CA (10000 Degrees, 2016). A program modeled this way does not provide the same type of information on postsecondary affordability to students, because an unknown third party controls the decision of aid award.

Lastly, a number of programs extended eligibility beyond a single school district or city. The extended boundaries lead to questions for how to geographically define a “community”. Changing the geographic focal point of the program adds degrees of separation between students and the program’s stakeholders. This eliminates the clear and direct line of communication for students to receive personalized eligibility information. The ability to receive a clear commitment is an important benefit of community-developed programs. Pluhta and Penny (2013) state that a local commitment to fund postsecondary education is received by students differently than large-scale programs, for example, Pell grants. Access to a direct source of information reinforces a student’s confidence in earning eligibility and is the catalyst to all other benefits.

A student who deems that higher education is not affordable alters his or her secondary school objectives and curricular choices. Heller describes this experience as cost discouragement (Goldrick-Rab, 2007; Glenn, 2004; Heller, 2006). Problems associated with postsecondary affordability extend beyond the amount of financial aid available to students, however. To acquire information on financial aid eligibility students must navigate barriers related to the limited time for gathering information on enrollment costs, the myriad of conditions used for financial aid eligibility, and the actually application process used to file for financial aid (Deming & Dynarski, 2009; Goldrick-Rab, 2012; Perna & Steele, 2011; Tierney & Venegas, 2009). Residency-based aid programs have been identified as one method of financial aid that can be used to overcome the barriers to misinformation on affordability (Andrews, 2013; Blanco, 2009; Harnisch, 2009; Schwartz, 2008; Tierney & Venegas, 2009). The following literature review outlines these issues and how residency-based financial aid programs have been used to lessen the burdens associated with acquiring information on postsecondary affordability for students.

Literature Review

I start by reviewing literature describing student's college choice decision-making process. Second, I describe issues related to acquiring information on postsecondary affordability, followed by a description of the application process for the federal financial aid, the Free Application for Federal Student Aid (FAFSA). Third, I identify circumstances that impact a student's sensitivity to financial aid. Lastly, I describe prior research on defining residency-based financial aid programs and detail the existing research on program outcomes.

College Choice. The examination of students' college choice has relied on the theories of two different academic disciplines: Economics and Sociology. Early examination of the decision to pursue higher education was treated as a consumer choice model. Economics' Human Capital Theory describes education as a student investing in his or her own intellectual capability leading to improved workforce productivity and higher workplace earnings (Becker, 1964; McMahon, 2009). Human Capital-based enrollment models make the assumption that students compare the potential return on investment from additional education against all implicit and explicit costs of attendance. When the perception of returns outweighs the accumulated costs, Human Capital Theory predicts a student will act to maximize their individual wealth by pursuing additional academic credentials.

Early sociological-based college choice models are different from Human Capital Theory. Sociological models consider what factors students use to make the college going decision and where a student accumulates information they use in making the decision.

Sociological-based models explain that student environment, background, and networks contribute to the decision to enroll. Bourdieu describes the amalgamation of environmental, social, and cultural forces as Habitus (Coleman, 1988; McDonough, 1997; Perna, 2006). In context to the college-going decision-making process, Habitus represents how students receive context on educational expectations based on experiences within their environment and through feedback obtained within their networks. The sociological perspective offers insight to why students from different racial and ethnic groups, unique upbringings, and dissimilar experiences may view the returns from education differently. Furthermore, it explains why students with varying level of resources may make different college going decisions.

The work of Hossler & Gallagher (1987) is considered one of the first, and most frequently cited, comprehensive models that outline the process students navigate to make the decision to enroll in postsecondary education (Bergerson, 2009). It builds from existing frameworks by Chapman (1981), Jackson (1982), and Manski and Wise (1983). Hossler and Gallagher (1987) explain college choice as the way "students move toward an increased understanding of their educational options," and how "individual and organizational factors interact" to contribute to the process (p. 208). Their model details student movement through three sequential stages: predisposition, search, and choice. The stages provide a linear framework for how students move from inquiring about postsecondary attendance, to a decision on enrollment, and if applicable, a decision on which institution to attend.

One criticism of Hossler and Gallagher's model is the failure to specifically include the influences of financial aid, financial aid accessibility, and price (tuition) sensitivities. Finances are embedded in multiple aspects of accessibility to higher education. St. John (2003) contends that a student must obtain financial access to higher education, as well as academic access. The availability of resources has a profound influence on college going decisions, such as the selection on where to enroll and the quantity of education to pursue. To model this interaction, St. John (2003) introduces financial aid into a college choice model labeled Balanced Access. Affordability shapes postsecondary aspirations and a student's level of academic preparation, in addition to the decision to enroll.

DesJardin, Ahlburg & McCall (2006) argue that financial aid is incorrectly treated as an exogenous variable. Financial aid awards are strongly correlated with other socioeconomic factors that models are conditioned on (DesJardin, Ahlburg & McCall, 2006; St. John, 2003). Various student characteristics predict financial aid availability, intertwining the financial and sociological aspects of college choice. To capture this, the authors develop a model formulation that includes the probability of financial aid in the application and enrollment process.

A critique of early stepwise college choice models is a lack of explanatory power on the actual decision that students make, how transition occurs between stages, and a timeframe in which transitions occur. Cabrera and LaNasa (2000) take Hossler and Gallagher's (1987) fundamental three-stage model and develop more clearly defined descriptions for when students advance through the model's stages. The Cabrera and LaNasa (2000) model identifies characteristics that connect the stages, explain how students advance through the process, and define the time parameters for when each stage is likely to occur. The predisposition stage starts with parent's motivational activities for students that usually occur in the pre-secondary schooling years of 7th and 8th grade. The search stage occurs later, between 10th and early in 12th grade. Lastly, the decision-making point is bound by the completion of secondary schooling at the end of the 12th grade year.

Perna (2005) provides a conceptual framework of multiple layers that organize where students receive information and context. Perna's framework breaks from the trend of describing students moving sequentially to a college choice decision, instead depicting a non-linear process of accumulated information and context. The process describes students gathering information and acquiring context through four contextual layers: *Social, Economic, & Policy Context*, *Higher Education Context*, *School & Community Context*, and *Habitus*. The accumulated feedback is then funneled into the core of the framework where the perceived rewards from additional education are weighed against both explicit and implicit costs from enrollment. The contextual layers capture Sociology's environment emphasis, and feed the result into a model similar to Economics' Human Capital Theory.

The college choice literature summarizes the process and factors that students use in the decision to pursue postsecondary education. Students psychologically adjust their perspective on school to become forward thinking somewhere between 9^{th} and 11^{th} grade (Bell, Rowan-Kenyon, & Perna, 2009). In this timeframe students establish aspirations for higher education, either developing a strategy for postsecondary admission or initiating actions toward other non-academic alternatives, such as entering the labor force or redirecting effort toward athletics. The exact point this evolution occurs is unknown and differs based on student characteristics (Cabrera & LaNasa, 2000; Perna, 2005). The models are limited in their ability to detail how information on postsecondary affordability may generate other college-choice decisions or impact the academic barriers to enrollment.

Acquiring Information on Financial Aid and Affordability. Dynarski and Scott-Clayton (2013) describe financial aid as a basic application of Economic principles - if the price of college is lowered, more people will elect to purchase a college degree (through purchasing additional college courses). The straightforward application of this principle assumes that the price of education is known upfront and students are capable of determining if they are able to afford the cost of attendance. This assumption may not hold for the demographic most in need of financial aid (King, 2004; Perna & Steele, 2011). Inaccurate information and limited understanding of how the financial aid system operates disproportionately hurts students from lower income households, underrepresented minority populations, and first generation students (Perna & Steele, 2011). This has confounding implications for financial aid programs targeting different student populations.

Elaborating on the multi-dimensional nuances of student financial aid issues, King (2004) describes how low-income students perceive they should be able to pay higher education expenses out of pocket. That is to say, those most in need of financial assistance believe that financial aid isn’t intended for them. Perna and Steele (2011) identify that the information a student accumulates may be creating a counterproductive, vague awareness. Particularly among underrepresented populations, students do not know how much they do not know. Students with some level of information (accuracy notwithstanding) may not recognize that acquiring additional information is necessary.

Navigating the price of higher education is also a challenge for parents. Few parents have accurate perceptions on the cost of higher education, regardless of prior higher education experience (Perna & Steele, 2011). In general, parents expect tuition rates to be higher than their actual rates. The tendency to overestimate the expected cost of attendance and underestimation financial aid eligibility exacerbates the perception of postsecondary education being unaffordable.

When families seek additional information, the methods they employ may inadvertently perpetuate the spread of inaccurate information. Students with low levels of social and cultural capital are susceptible to limited alternatives, or awareness of alternatives, for acquiring information; for instance, limited Internet access for low-income populations (Deming & Dynarski, 2009; Tierney & Venegas, 2009). This issue is compounded when school districts are faced with constraints, such as understaffing. The information constraint from limited resources can cause students to navigate through inefficient channels to gain personalized information, such as seeking information from friends, and seeking information from teachers and coaches over college representatives. (Flint, 1993; Heller, 2006; Hossler & Vesper, 1993; McDonough & Calderone, 2006; Perna, 2006; Tierney & Venegas, 2009). The difficulty in acquiring accurate information produces a network where erroneous information is continually cycled among students.

When parents begin with limited financial aid knowledge they are less likely to feel confident in the accuracy of any new information they receive. One reason for this may be limited trust in the source of information, but another reason may be the source providing financial aid. Trust issues can be embedded in underrepresented populations and have ramifications beyond promoting accurate information. Mistrust is a function of past experiences with social programs and is projected onto other social benefits, such as financial aid. This is true even when eligibility is straightforward, such as with residency-based aid programs. Penn (2012) finds that parents and students are skeptical of the financial aid offered through the Kalamazoo Promise. Penn describes that African-American parents believe the scholarship was a trick, the award comes with unstated expectations (a "catch"), the award was actually "not for us", or that aid would be "snatched" away at the last minute (2012, pg. 12).

Barriers exist in navigating and deciphering financial aid information after obtaining details on eligibility. Deming and Dynarski (2009) describe a "tradeoff between targeting and program effectiveness" that results from the large number of financial aid programs that exist and the inconsistent eligibility criteria (pg. 16). Doyle (2008) describes that the effort to target aid specifically to students with financial need leads to an increased number of eligibility criteria and causes excess confusion. Similar arguments have been made regarding all social welfare programs (Mumper, 2003; Porter, 2015).

The Financial Aid Application Process. Eligibility for financial aid does not automatically equate to being awarded financial aid. The process of applying for financial aid is particularly sensitive to timing and demonstrating eligibility, specifically the federal application process used to allocate federal aid. The Free Application for Federal Student Aid (FAFSA) application requires students to submit personal information (such as student assets and family resources) to determine how much tuition and fees will remain after a student has exhausted their personal and family resources. The annual application uses household responses to calculate the Expected Family Contribution (EFC) for each student.[2] EFC is an estimate of how much monetary support can be provided by the household to cover postsecondary expenses.[3] The results of a student's FAFSA application are used to determine eligibility for a large number of state, local, and institutional financial aid programs, in addition to all federal-based aid awards (Dynarski & Wiederspan, 2012). In total, the information collected through FAFSA is

[2] See Dynarski and Wiederspan (2012) for a complete review.
[3] This does not necessarily mean that a family will devote these resources. A student must include information on guardian's wealth until the age of 24, unless the emancipation process has occurred or they have a child. This is regardless of whether the student is claimed as a dependent on income taxes, or whether the student lives in the household.

responsible for determining as much as three-quarters of all financial aid dollars (Dynarski & Wiederspan, 2012).

The FAFSA form may be submitted as early as a student's junior year of high school containing income tax information from the year prior (Supiano, 2015). The timing corresponds with the late stages of the college choice process and potentially beyond the point at which a student can reevaluate their academic decisions (Cabrara & LaNasa, 2000; Dynarski & Scott-Clayton, 2013; Kelchen & Goldrick-Rab, 2012; Plank & Jordan, 2001). Students are likely to have already made an enrollment decision by the time they receive confirmation on postsecondary affordability (Dynarski & Scott-Clayton, 2013). The late notification of eligibility reduces the college-going decision to a narrow decision set: accept the aid package offered by the accepting institutions, enroll in an open-enrollment institution, or delay enrollment. For example, accepting the aid package may include student loans introducing the potential for student debt. To this point, Heller (2006) argues that students may not fully understand the trade-offs for accepting different financial aid programs until after they have been awarded.

Student Price Sensitivity. Generally, research finds that financial aid has a positive effect on postsecondary enrollment (Heller, 1997; Leslie & Brinkman, 1987). The degree of this relationship is difficult to discern because of inconsistencies in research findings and complicated realities. Heller's (1997) research raises the question whether students view all financial aid equally, specifically identifying the existence of a greater responsiveness to grant aid, relative to loans or work-study programs. In addition, sensitivity to financial aid is differentiated based on student characteristics such as race, ethnicity, and income status.

Sensitivity to the amount of financial aid offered may be a function of the availability of resources (Heller, 1997; Paulsen & St. John, 2002). Van der Klaauw (2001) finds that underrepresented student populations likely have higher enrollment elasticity toward financial aid. Small financial aid incentives represent a large proportion of a low-income student's overall resources. As a result, small changes in aid offerings are perceived as large monetary incentives and impact the probability of enrollment drastically. The degree of sensitivity is diminished for students from higher income households likely because comparable aid awards represent a smaller share of total resources.

Differences exist in sensitivity to the financial aid form in which an award is presented, dependent on race and ethnicity. A direct, positive relationship is found between federal aid amount and minority enrollment, particularly among African-American and Hispanic students (St. John, 2003; St. John & Noell, 1989). African-American students do not exhibit different levels of responsiveness to financial aid based on household income (Paulsen & St. John, 2002). Heller (1997) attributes this to the role cultural values play in viewing potential trade-offs, such as foregoing higher education and entering the labor force.

Hispanic students demonstrate distinctive trends in aid sensitivity. In particular, Hispanic students appear acutely sensitivity to student loan offerings. Burdman (2005) observes that they are less inclined to attend a postsecondary institution if it means accumulating any amount of student debt. Bers (2005) finds that only about one-third of students who attend traditionally, low cost community colleges applied to other institution types. Rodriquez, Guido-DiBirto, Torres and Talbot (2000) describe that Hispanic students will opt to enter the workforce instead of accepting financial aid packages that include student loans. McDonough and Calderone (2004) and Perez (2010) assert that this choice is explicitly to avoid any amount of debt.

Typically, financial aid research examines the impact from a specific financial aid format or financial aid amount. Responsiveness to financial aid is not just a function of the format or amount of aid, but also includes the timeframe in which students receive affordability information. Time is a necessary resource in developing college readiness characteristics for students. The opportunity costs of postsecondary enrollment offset financial aid awards when students do not perceive they are capable of being academically successful (Perna, 2004). Students are less capable in adjusting academic outputs, such as increasing grades or standardized test scores, in shortened timeframes (Fryer, 2011; Kelchen & Goldrick-Rab, 2012; Plank & Jordan, 2001).

Fryer (2011) tests a series of financial stimulants designed to assess academic outcomes in urban, predominately low-income schools through the use of input and output-based reward systems. Fryer's (2011) research was based on a secondary school "pay for grades" incentive. Fryer (2011) concludes that students are more receptive to input-based rewards because of existing shortages in educational capital and resource availability. Output-based incentives are largely ineffective if students have limited prior experience in identifying and alleviating academic deficiencies in a short-term timeframe. Students who have limited prior experience turning motivation into outcomes recognize that they are not able to identify how to achieve this in a short timeframe, and as a result, are less likely to be incentivized by an output dependent incentive.

Fryer's research uses a financial incentive different from financial aid but still has implications on issues related to information on postsecondary affordability. Fryer's research raises the question on whether incentives in the latter years of high school are sufficient to promote positive academic outcomes. Students who are guided away from an academic mindset in early high school may require a larger motivation to reconsider higher education and this may not provide enough time to become academically prepared.

The literature outlined above describes how student information on postsecondary affordability and the time they receive this information may have a broad array of consequences beyond college enrollment, including secondary school outcomes and behaviors. Residency-based aid programs have characteristics that may provide students with transparent, advanced information on postsecondary affordability (Andrews, 2013; Blanco, 2009; Harnisch, 2009; Schwartz, 2008; Tierney & Venegas, 2009).

Defining Characteristics of Residency-Based Financial Aid Programs. Next, I review how previous research has described and labeled programs with residency-based stipulations. I begin by outlining the defining characteristics described by past authors. Three major areas are given emphasis in the literature: the timing for when the commitment is provided, how to address the use of secondary non-residency-based qualifications to target specific student demographics, and the role of geographic region in developing programs. Afterward, I review another typology created to categorize residency-based aid programs and describe how my research contributes to the literature.

Timeframe. Time is relative in regard to financial aid. For financial aid, "early" is typically expressed in terms of receiving feedback on the FAFSA application. FAFSA submission requirements do not allow students to learn about the aid award, and affordability, until their late high school years. The timing of financial aid information is beyond the point when students may begin to alter their postsecondary expectations. Researchers assert that time is essential for students to comprehend the information provided by financial aid programs (Schwartz, 2008). Understanding the characteristics and benefits of a program are necessary to incentivize positive academic and social adjustments (Blanco, 2009; Harnisch, 2009; Kelchen & Goldrick-Rab, 2012; Tierney & Venegas, 2009; Vaade, 2009). When early information on aid eligibility is clear and provides certainty in affordability, students have greater confidence in making curricular decisions and improving college readiness.

Residency-based aid programs are typically associated with early information on affordability because of the transparent eligibility criteria and their commitment to fund all eligible students. Transparent, upfront information on the requirements for eligibility allows a student to accurately estimate and continuously reassess their eligibility before formally applying for aid. Harnisch (2009) describes a benefit of early commitment programs as the ability to “alleviate real or perceived cost barriers to postsecondary education through offering a contract that clearly spells out the terms needed to qualify for college admission and state financial assistance” (pg. 3). Harris and Orr (2013) state “by increasing real and perceived affordability of college, and clearly communicating the path to college, the theory is that these early commitment programs improve academic preparation and social capital” (pg. 1).

Researchers have differed on when information from a residency-based aid program must be provided to students in order to receive the benefits from advanced information on affordability. Andrews’ (2013) describes that students must obtain information in a point in time before they have made a decision on postsecondary enrollment. Schwartz (2008) requires only that information be available prior to a student’s 11th grade year. Blanco (2009) describes early information in relation to the decisions associated with academically preparing for college, stipulating that information on eligibility must be provided in the first years of high school.

***Secondary Qualifications*.** Some programs attempt to restrict the eligible student population, or reward a specific student group, by targeting which students receive the aid award. Targeting a specified demographic is achieved through adding secondary eligibility qualifications beyond residency. The variation among secondary qualifications blurs the division between merit- and income-based financial aid programs, which has implications for program comparisons (Andrews, 2013; Ash, 2015; Bozick, Gonzalez, & Engberg, 2015; Miller-Adams, 2015). Residency-based aid programs may be useful to incentivize a specific student demographic, for instance, students who perceive higher education as unaffordable. For economically disadvantaged students, an early commitment for financial aid removes fiscal roadblocks present in the college-going decision and encourages postsecondary academic preparation (Blanco, 2005; Harris & Orr, 2013; Tierney & Venegas, 2009). Removing financial obstacles fosters the idea of educational attainment and creates a college-going culture among the community (Bozick, Gonzalez, & Engberg, 2015; Harnisch, 2009; Harris & Orr, 2013). Tierney and Venegas (2009) are among a group of scholars who generalize early commitment programs as need-based, specifically targeting economically disadvantaged students.

Blanco (2009) uses early commitment to signify an “umbrella descriptor for a wide variety of programs that target low-income students while they are in middle or high school” (pg. 1). The author describes these programs as a relationship to uphold certain qualifications in return for the promise of aid, helping to eliminate financial anxiety while still promoting academic preparation. Vaade and McCready (Vaade, 2009; Vaade, 2010; Vaade & McCready, 2011) distinguish between Universal and Targeted aid. The authors discuss a variation of early financial aid programs using the term Postsecondary Opportunity Programs (POPs). They define such programs as containing any mixture of need-based aid, merit aid, or universal aid, so long as non-monetary benefits such as mentoring are also included.

***Geographic Region*.** The capacity to generate economic benefits is a component of residency-based aid programs. Economic development was a point of emphasis in creating early programs, such as the Kalamazoo Promise (Miller-Adams, 2015). According to Economics’

Human Capital Theory, improved educational access has preventative and curative influences on social welfare needs (Becker, 1964; McMahon, 2009; Schwartz, 2008). Harnisch (2009) notes that policymakers may use residency-based programs as a tool to capture students who are not influenced by other social benefit programs.

The geographic alignment of social and educational benefits is important. Programs with residency-based eligibility act similarly to social policy mechanisms (Andrews, 2013; Schwartz, 2008). The relationship between economic development and geographic boundaries is described as influential for developing a reliable revenue source (Andrews, 2013). Researchers have stated that programs with different geographic sizes (size being a measure relative to the eligibility boundary) stimulate different levels of incentives. Programs smaller than state eligibility stimulate localized economic returns (Andrews, 2013; Blanco, 2009). Programs with broader statewide residency eligibility typically act as a policy tool for larger social purposes (Andrews, 2013; Blanco, 2009).

***Typologies*.** Perna and Leigh (2017) develop a typology for organizing and categorizing existing programs with residency-based qualifications. The authors use five primary criteria for program inclusion in their typology: programs must designate higher education access as the primary objective, programs must offer a "promise" of financial aid to eligible students, programs must clearly define "place" as residency within a state or a geographic subset within a state, programs cannot be catered to students within a specific demographic or for students seeking specific postsecondary credentials, and programs must provide clear information for eligibility. Perna and Leigh's (2017) typology examines 289 programs.

Perna and Leigh (2017) use cluster analysis to identify six distinct groups of programs. The group distinctions are based on state and local geographic region, the type of institution aid that can be redeemed, and how broadly residency is defined. They label the six resulting groups as State-Sponsored, Unrestricted, Merit-based (Type I); State-Sponsored, Unrestricted, Need-based (Type II); State-Sponsored, 4-Year, Last Dollar (Type III); State-Sponsored, 4-Year, Merit-based (Type IV); Universal Eligibility (Type V), and 2-Year, Last Dollar (Type V). The authors describe the six groupings as a meaningful starting point for new research on Promise programs. Each group contains program with operational characteristics fundamentally dissimilar from programs in other categories.

There are important differences in the research presented in Perna and Leigh's (2017) typology and the typology I present here. The differences between the two typologies lead to differing results and allow each to contribute meaningful knowledge on residency-based aid programs. First, there are differences in the qualifications used for including programs in each sample after accounting for residency and transparent eligibility criteria. Perna and Leigh include programs that have not begun distributing funding. This adds to the sample size of their research, but it captures programs that have not yet made final operational decisions. These programs may still experience changes that fundamentally alter their structure and mission or that cause them to never commence distributing aid. Removing these programs, or altering their characteristics, can have impact on the cluster analysis methodology (Everitt, Landau, Leese, & Stahl, 2011). In contrast, I focus on programs that have finalized operational procedures and are currently providing financial aid to students. As a result of the sampling decisions, the cluster analysis results I present are groups of programs that are distributing financial aid, not clusters of programs with similar designs.

Perna and Leigh (2017) opt to exclude programs that formally state economic development as their primary motive and programs funded directly by postsecondary institutions (typically called No Loan programs). Omitting these programs makes it unclear how they may have distinction from residency-based aid programs and does not offer insights into how they should be compared in research. I include each of the previously described program types. This decision allows my clustering results to contribute to the fields understanding for how to treat programs with a residency-stipulation but that may not typically be considered residency-based aid programs.

The authors discuss that future researchers should explore “whether a program creates early commitment to or awareness of program benefits and requirements”. The typology I present here addresses this need by identifying the operational procedures, the specific groupings that each program is clustered into, and addressing the hole in the literature regarding program comparisons. The typological groups directly address which programs are comparable and the specific areas of comparability with regard to early information on postsecondary affordability.

Student Outcomes from Residency-based Scholarship Programs. An affiliation between the W.E. Upjohn Institute and the Kalamazoo Promise has produced a disproportionate amount of research on this particular program. Research corresponding to the Kalamazoo Promise has centered on secondary school outcomes, evolution of the local culture, college choice, and postsecondary outcomes. I outline the Kalamazoo Promise research first, followed by research of other individual programs with redeemability at 4-year institutions. A comprehensive review of programs with eligibility at 2-year institutions can be found in the literature review for Paper Two.

The Kalamazoo Promise announcement transfers Kalamazoo student’s post-high school decision-making process to a timeframe earlier than 11th grade (Penn, 2012). The scholarship can inspire a fundamental shift in postsecondary aspirations and is most profound for student populations with relatively little understanding of educational returns. The program is associated with positive impacts related to student's secondary school effort and academic outcomes (Bartik & Lachowski, 2012). In the three years after the announcement, Bartik and Lachowski (2012) find that the average number of student suspension days decreased by over one day. One explanation proposed by the authors is that students were present in class more frequently, which limited the amount of time available for undesirable behaviors. During the first three years of the scholarship, student GPA's did not significantly change; though when disaggregated by race, there was evidence of a slight GPA increase for African-American students (Bartik & Lachowski, 2012). Bartik, Eberts, and Huang (2010) find statistically significant gains in reading for the entire school district and mixed results in Mathematics scores. Despite the limited improvements in student grades, increased demand necessitated the addition of more Advance Placement courses and a new college readiness-based curriculum (Miller-Adams, 2010; Miller-Adams, 2011).

The incentives from the Kalamazoo Promise extend to a culture change for the community. Bartik, Eberts, and Huang (2010) identify that the announcement of the program reversed the outward migration of Kalamazoo's population and enrollment within the school district. Hershbein (2013) follows up this research by identifying that the new student population mostly came from the immediate area, Kalamazoo County, but out of state migrants made up a statistically significant 25% of new enrollees. Surprisingly, only a small number of students switched from non-eligible schools within the City of Kalamazoo. Hershbein's (2013) results on whether the new student population was more affluent are mixed. There is no statistical difference in income level for families that migrated into Kalamazoo after the scholarship was announced. Miller-Adams (2010; 2011) details that the first successful bond election was passed allowing for the construction of the district's first new schools in forty years. Parents increased their level of participation in school activities strengthening the levels of social and cultural capital among the community (Miller-Adams, 2010). Additionally, local business leaders contributed funding to develop a tutoring services center for students (Miller-Adams, 2010).

To determine if there was an influential impact on institutional choice, Andrews, DesJardins, and Ranchhod (2010) conducted a quasi-experimental design immediately following the Kalamazoo Promise announcement. The authors determine that students became more likely to send standardized test scores to the state land grant institution (Michigan State University) and less likely to send them to the in-district community college (Kalamazoo Valley Community College). Andrews *et al.* (2010) make the argument that this is evidence that the expected cost of tuition is a significant determinant in how students made decisions on applying to potential institutions. This reasoning is especially prevalent given that students may send test scores to six different institutions for no additional charge. Post-Kalamazoo Promise enrollment trends support the conclusion of Andrews *et al.* (2010). The W.E. Upjohn Institute (2015) presents statistics for increased enrollment across all institution types in the state of Michigan. Enrollment gains were most pronounced at the two local, public college campuses, including Kalamazoo Valley Community College and Western Michigan University. The enrollment influence is also evident in the state flagship institutions Michigan State University and the University of Michigan-Ann Arbor (W.E. Upjohn, 2015).

The immediate changes from the Kalamazoo Promise extend into long-term effects. The increase in postsecondary enrollment described in earlier studies remains present after nine graduation classes (Bartik, Hershbein, & Lachowska, 2015). Bartik, Hershbein, and Lachowska (2015) show an 8-percentage point gain in enrollment and a shift to public, in-state four-year institutions. A notable difference from the early years of the program is a substitution away from both two-year institutions and out of state alternatives (Bartik, Hershbein, & Lachowska, 2015). Plausible explanations for the enrollment shift are the longer time period in which students have information on affordability, in addition to the changes in availability of tutoring networks, increased parent participation, and movement toward a college-preparation curriculum.

The Kalamazoo Promise has implications for postsecondary outcomes. After enrollment, students exhibit increases in credit hours attempted and degree completions (Bartik, Hershbein, & Lachowska, 2015). Kalamazoo Promise recipients acquired 15% more credit hours, earned four-year degree credentials at a 9% higher rate, and earned other postsecondary credentials at an 11% higher rate; all relative to non-recipients. Bartik, Hershbein, and Lachowska (2015) find that the degree earning results are consistent across income groups. Low-income students are equally as likely to earn more credit hours and achieve a postsecondary credential, as higher income students.

A program often compared to the Kalamazoo Promise is Arkansas' El Dorado Promise. The El Dorado Promise offers between 65-100% of tuition and fees to students who graduate from an El Dorado public school, using a percentage scale similar to the Kalamazoo Promise. Unlike Kalamazoo, El Dorado's scholarship can be used at any two or four-year institution within the United States. Ash and Ritter (2016) find that within the school district, staff and personnel elevated the expectations for students after the program was created. This included placing more emphasis on increasing postsecondary awareness and promoting access through college preparatory coursework.

The El Dorado scholarship announcement had positive outcomes on student achievement in high school (Ash, 2015; Ash & Ritter, 2014). Students significantly increased both math and literacy scores relative to students' from the time period before the El Dorado Promise. Specifically, low-income and African-American students made the largest gains in these areas, but only those who were previously in the top half of scores. Placing these results into perspective, Ash (2015) describes the gains from the program announcement offset the expected lower scores among students who qualify for Free/Reduced lunch. After the scholarship announcement, there is no statistical difference in test scores between economically disadvantaged students and their more affluent classmates.

Ash and Ritter (2014) determine that high school graduation rates are not statistically influenced by the scholarship, despite the improved academic performances. No discernable difference exists in high school graduation rates pre- and post-El Dorado announcement, overall. There is evidence that low-income students may actually graduate at lower rates after the announcement. This could be an unintended consequence of the school district's push towards a more academically rigorous curriculum. Students are not fully able to transfer the increased efforts into academic outputs, in the short term.

The Pittsburgh Promise differs from both Kalamazoo and El Dorado in the distribution of aid. The Pittsburgh Promise will fund up to $10,000 per year for students who graduate from an approved Pittsburgh high schools with a 2.5 GPA and have at least 90% attendance (Gonzalez, Bozick, Taylor, & Phillips, 2011). The actual aid award is dependent on the student's length of residency within the specified Pittsburgh school districts and is redeemable at any public or private, two- or four-year institution within the state of Pennsylvania. Unlike the Kalamazoo Promise there appears to have been no new migration into the city following the announcement (Gonzalez, Bozick, Taylor, & Phillips, 2011). Instead, parents use the availability of the scholarship to determine which secondary schools to enroll their child. The finding of secondary school choice is most pronounced among minority households, parents with low levels of education, and low-income households.

The program structure of the Pittsburgh Promise creates different student incentives regarding institutional choice (Bozick, Gonzalez, & Engberg, 2015). Students are less likely to enroll at a postsecondary institution following high school with the benefit of the Promise scholarship, however they are more likely to enroll at four-year institutions. Gonzalez, Bozick, Taylor, and Phillips (2011) describe that students are using the program to gauge their postsecondary readiness. One possible reason for this finding is that the minimum grade point average for program eligibility may be providing affordability information to students with higher grades who already planned to attend college.

Residency-Based Financial Aid Program Sample Population

Cluster analysis is a useful technique to identify natural groupings of objects with similar characteristics. Specific to this research, cluster analysis is used to identify groups of comparable financial aid programs where student eligibility is defined (in part) by geographic boundary. A necessary first step in this process is the identification of programs to be examined. Next, I describe the process for collecting a list of sample programs. Then, I describe the multiple program characteristics I require for inclusion in the sample population of the typology. Lastly, I detail the process of examining programs and creating the dataset to be used in the cluster analysis.

Sample Collection Process. I use a multi-step process for accumulating a sample of residency-based aid programs. The different steps are used to collect a large sample of programs and avoid any potential bias in the sample of programs and characteristics, for example, only identifying programs with the largest endowments to fund scholarships. Programs with large coffers may receive more public attention but are not necessarily representative of all residency-based aid programs. To identify similarity across groups of programs, it is important to have a sample population with extensive variation.

To identify a list of potential programs, I begin by referencing the list of programs created by the W.E. Upjohn Institute (2017), the Cities of Promise (2017), and Civic Nation (2017). The three organizations support research and offer consultation on new Promise program development. The W.E. Upjohn Institution (2017) defines residency-based aid communities as making a "long-term investment in education through place-based scholarships" seeking to first "expand access to and success in higher education" while creating support for local economic development. The Cities of Promise identify Promise programs as a subcategory of place-based aid (Cities of Promise, 2017). The Cities of Promise database includes only scholarships with "an expectation of local economic development" (Cities of Promise, 2017). Civic Nation's College Promise Campaign (2017) is national program to build public support for programs which, "guarantee tuition and fees for eligible, hardworking students to complete a college education." The benefit of using the three databases is that I am able to capture a larger number of programs and programs with different primary missions (postsecondary access and economic development).

Next, I include programs previously referenced in scholarly research. I identify articles by keyword searches: "early commitment," "place-based aid," "Promise programs," and "universally eligible." The format labels are commonly used in prior research of programs with residency-based requirements. Also, I search for articles that reference three specific programs: Kalamazoo Promise, El Dorado Promise, and Pittsburgh Promise. I use the three programs because of the national attention received by each. Publications (both scholarly research and popular media) frequently use the three programs as a reference or in providing context for information on other programs. Including the three programs in the keyword search was also beneficial in finding additional articles that used program labels that did not align with the keyword search. For instance, Vaade (2009) labels similarly structured residency-based programs as Postsecondary Opportunity Programs.

I gather a list of programs using the keywords “financial aid programs + ” and add the terms “promise”, and “place-based” in a general internet search. From this search, I have found two unique websites that list financial aid programs by format category: College Greenlight and FinAid.org (College Greenlight, 2017; FinAid, 2017). The websites are designed to help students identify potential scholarships, and they contain links to the additional information for each program.

Lastly, I include financial aid programs previously characterized as institutionally based and state-based aid programs. A number of institutions have begun adopting financial aid policies designed to decrease the out-of-pocket cost of attendance for students in a designated local, geographic region (Linsenmeier, Rosen & Rosue, 2006; Lips, 2011; van der Klaauw, 2002; Waddell & Singell, Jr., 2010). This format is called No Loan programs (Linsenmeier, Rosen & Rosue, 2006; Lips, 2011; van der Klaauw, 2002; Waddell & Singell, Jr., 2010). I identify No Loan programs through scholarly articles and a general internet search of scholarship websites using the keywords “No Loan”.

State-based aid programs inherently have residency-based eligibility qualifications. To identify state-level programs, I use the Education Commission of the States’ (ECS, 2015) *State Financial Aid Redesign* database. ECS’ *State Financial Aid Redesign* database includes a policy scan of the top 100 funded programs across all 50 states. In using the top 100 policy scan, I assume that a state-level financial aid program that does not use an individual selection process to award aid would be among the highest-funded financial aid programs in the state. This assumption is based on the belief that the number of potential college-going students within any state is substantial enough to require funding greater than programs that select a defined number of students each year.

I include No Loan programs and state-based aid in this typology to serve as a robustness measure of the cluster analysis. The defining characteristics of residency-based aid programs outlined in the literature review could be used to describe state-based and No Loan programs. (Andrews, 2013; Ash, 2015; Bozick, Gonzalez, & Engberg, 2015; Daun-Barnett, 2011; Miller-Adams, 2015; Tierney & Venegas, 2009; Vaade, 2009; Vaade & McCready, 2011). In addition, programs from both categories have been described as comparable to community-sustained programs (Andrews, 2013; Blanco, 2009; Miller-Adams, 2015; Vaade, 2009; Vaade & McCready, 2011). Despite the previous comparisons, there may be fundamental differences across program types that cause students to respond differently to the program. Specifically, the eligibility criteria for No Loan and state-based aid programs may not provide the same amount of transparency for students as a local community-sustained program. By including both formats in the typology, I hope to find evidence that the three types of financial aid programs are dissimilar enough to be placed in different comparison groups.

Sample Program Criteria. After amassing a list of sample programs, I examined the available information for each program prior to the 2016-2017 academic year. This step included creating an archive of documents, reports, applications, and flyers. When important characteristics were missing or unclear, I attempted to personally communicate with administrators through program "contact" links and search for media publications about the program. The archive of documentation is used to assess the unique characteristics of each program, operational practices, descriptions of the students served by the program, and intended commitment to providing funding to all eligible students.[4]

Creating a typology requires researchers to make decisions on scope, breadth, and program inclusion. This is an important and unavoidable endeavor for creating any typology (Perna *et al.*, 2008). The focus of this typology is to identify groups of residency-based aid programs that are comparable based on the information they provide to students regarding postsecondary access and affordability. I use the following three selection criteria to distinguish residency-based financial aid programs from organizations/programs that have previously been associated with providing financial aid: defined geographic boundary, pre-2016 start date, and clearly defined eligibility criteria.

First, a program must directly identify the geographic boundary for eligibility. The residency boundary may be a specific state, or a list of counties, cities/municipalities, or school districts. Residency is a transparent criterion when the boundary is clearly stipulated. Residency or longevity is easily discernible by students who are seeking to estimate their eligibility.

Second, I include only programs that advertised a start date prior for the 2016-2017 academic year or before. I define a start date as the first year that financial aid is awarded based on the programs eligibility criteria. The desire to develop a residency-based aid program does not guarantee that the program will not require design changes. The resources available to a program dictate the number of students who can be served (Andrews, 2013; Mumper, 2003). A program intending to reach a specified student population may fall short of the resources necessary to

[4] Appendix C contains a list of websites used to identify characteristics for each program included in the cluster analysis. Websites include formal program websites, program's facebook pages, links to press releases, and videos used to introduce programs.

achieve this, resulting in the program being delayed or fundamentally changing characteristics. Each of these obstacles alters the actual operational procedure and eligibility criteria that are used by the program. For example, city council funding was approved for the Milwaukee Promise in 2014 after years of planning, yet the program has not been finalized (OnMilwaukee, 2014).[5] Any changes to the factors used to identify an entity (operational procedures for a program, in this instance) can fundamentally change the grouping process in a cluster analysis (Everitt, Landau, Leese, & Stahl, 2011).

Third, building from the above requirement, all programs must state upfront the criteria used for awarding aid. The purpose for this is to isolate competitive aid programs that select students based on individual characteristics or that use an application process and award aid based on undisclosed criteria. The criterion used for eligibility is an important component of students being able to estimate their eligibility (Daun-Barnett, 2011). Students cannot estimate their chances of achieving postsecondary affordability without advanced knowledge of what benchmarks must be met. Transparency is why residency-based aid programs are frequently associated with early information on postsecondary affordability (Andrews, 2013; Kelchen & Goldrick-Rab, 2013; Pluhta & Penny, 2013).

Sample Data Description. In total, several hundred programs were examined for inclusion, but only 199 met the three criteria stipulated above. Awarding aid based on an individual selection process or using unknown criteria were the most common reasons for excluding state-based programs. Only 43 of the top 100 state-based programs were included from ECS' *State Financial Aid Redesign* database (2015). Programs in the developmental stage

[5] The planning for the Milwaukee Promise occurred separately from the Degree Project and the MATC Promise in Milwaukee.

that have not begun to distribute aid are the most common reason for omitting community-level programs.

After identifying the programs to be included in the sample, I examine the resources to identify the variation among the programs' operational procedures. I use the information accumulated for each program to create a cross-sectional dataset consisting of 12 binary variables. The 12 dichotomous variables are each structured as questions with the coding *Yes*= 1 and *No*= 0. Fundamentally, the variables are designed to capture program decisions that are made with respect to the specified geographic location for eligibility, the timeframe when students earn eligibility, decisions on the program's value and aid distribution, additional qualifications for eligibility, and specifications for redeemable institutions. The variables represent information available to students regarding their eligibility, their potential award, and how/where they may use the aid. Table 1 summarizes the dataset and cluster analysis results for all 199 programs examined for the typology. Next, I describe the specific variables and the reasons for using each.

Geographic Scope. *City* identifies whether the geographic region for eligibility is a county, city, or high school (if yes, *City*= 1; if the boundary is larger than a specified city/county, *City*= 0). This category is useful in addressing how to classify the size of residency parameters and in determining community and population responses to the program (Bartik, Hershbein, & Lachowska, 2015; LeGower & Walsh, 2014; Miller-Adams, 2011). A well-defined parameter allows program organizers to create an epicenter for the social benefits a program may generate (Miller-Adams, 2015). Additionally, geographic scope may have important implications for how a student responds to the program's creation (Pluhta & Penny, 2013). The geographic span for program eligibility may be significant to isolate differences in student demographics, economic conditions, and secondary school resources that could bias research results.

Timeframe. *Early* denotes whether students begin the eligibility process before starting 9th grade (if yes, *Early*= 1, if eligibility is determined after the start of 9th grade, *Early*= 0). Decisions made during this timeframe could have an influence on how students assess their likelihood of being successful in college and their decision to enroll and may have implications for the amount of time needed to adjust curricular decisions or social behaviors (Duan-Barnett, 2011; Fryer, 2011; Perna, 2004; Perna, 2005; Perna & Steele, 2011). When eligibility is based solely on longevity of residency, *Early*= 1 because students can estimate their eligibility as early as kindergarten. For programs that do not use longevity of residency, *Early* is determined by the year the student signs a contract/pledge to enter the program or begin the first steps to earn eligibility. *Commit* describes whether the program guarantees aid award to all eligible students (if yes, *Commit*= 1). The commitment to fund all eligible students is an important signal of postsecondary affordability for students and a critical component in college choice models (Blanco, 2005; Blanco, 2006; Cabrera & LaNasa, 2000; Harnisch, 2009; St. John, 2003; Tierney & Venegas, 2009).

Value. Three formats for distributing aid are used across programs: Unmet Need (*Last Dollar*) funding, *Percentage* of the cost of attendance, and *Flat* value aid award. *Last Dollar* identifies whether aid will cover all remaining unmet need without students having to obtain students loans. *Percentage* describes programs that distribute aid as a percent of the cost of attendance. *Percentages* are most commonly based on the longevity of residency. *Flat* value aid award signifies programs that award a single pre-determined aid amount that does not change based on postsecondary choices. No previous author has discussed the value of the aid awarded, but Ash (2015) notes a distinction across program types. I believe this is a clear omission and is relevant to understanding student outcomes across programs. Differences in aid award amount can influence a student's college-going decision (Heller, 1996; Leslie & Brinkman, 1989). In addition, the method for which aid amount is determined might create differences in a student's perspective for enrollment. The three value variables are mutually exclusive of each other. All programs are coded Yes= 1 for exactly one option.

***Sub-Qualifications*.** The uncertainty in classifying programs with multiple qualifications is raised in other residency-based aid literature (Andrews, 2013; Bozick, Gonzalez, & Engberg, 2015; Doyle, 2008; Harnisch, 2009; McPherson & Schapiro, 2010; Miller-Adams, 2015; Mumper, 2003; Tierney & Venegas, 2009). Beyond residency, a number of programs incorporate additional qualifications for eligibility (I term, *Sub-Qualifications*). The most common *Sub-Qualifications* are based on student academic standing and financial need. *GPA* identifies whether the programs uses a specified minimum high school GPA requirement (if yes, *GPA*= 1). *ACT* identifies whether a minimum score on the standardized test is required for eligibility (if yes, *ACT*= 1). *Income* designates programs with a specified minimum household income requirement to be eligible (if yes, *Income*= 1). The inherent problem with using stipulations to isolate beneficiaries is that the targeted population often does not perceive that they are eligible (Doyle, 2008; Mumper**,** 2003). When the number of qualifying stipulations for a program increases, it creates more vagueness for students in estimating the likelihood that they will be eligible. Duan-Barnett (2011) labels this uncertainty "risk" of not achieving eligibility. Fundamentally, a risk of not achieving eligibility limits a student's ability to use early information on affordability.

***Institutional Type*.** *Select* identifies whether the scholarship is redeemable at a specific subset of institutions that does not extend to all public or private colleges within the state. This is determined based on the description for where students may use aid. *2-yr* and *4-yr* identify whether each respective institution type was included in the list of redeemable institutions. If only specific institutions were identified, I used the website for each college to determine what types of degrees were awarded. Institution type may have a number of influences on how students respond to the program. The number and type of institutions where aid may be redeemed changes the institutional choice for a student (Andrews, *et al.*, 2010; Bartik, Hershbein, & Lachowska, 2015; Bozick, Gonzalez, & Engberg, 2015; Carruthers & Fox, 2016).

Cluster Analysis Methodology

Cluster analysis is a means to observe segmentation among a specified population. Cluster analysis has a broad range of applications, from identifying the herding behavior of mammals to demonstrating the motivating factors of marathon runners (Everitt, Landau, Leese, & Stahl, 2011; Ogles & Masters, 2003). Clustering is used in postsecondary research to explore engagement patterns for community college students, identify institutional No Loan programs, and categorize institutional responsiveness to developmental education reform (Lips, 2011; Park, Tandberg, Hu, & Hankerson, 2016; Saenz, Hatch, Bukoski, Kim, Lee, & Valdez, 2011).

I use three different hierarchical clustering approaches in this typology, Average linkage with coefficient matching, Weighted-Average linkage, and Ward's linkage. Each method is agglomerative, so programs start in isolation and are added to a cluster based on a similarity calculation. Each of the three methods has distinct advantages and disadvantages that apply to this typology.

The Average linkage approach calculates the distance between two groups using the average similarity calculation for programs within each group. The matching coefficient provides full weight to exact matches in the groupings (Everitt, Landau, Leese, & Stahl, 2011). Weighted-Average linkage is an adaption of the Average linkage. The notable exception is that as the sizes of clusters change, the weight for exact matches is reduced. This tactic is beneficial when clusters do not have a uniform population (Everitt, Landau, Leese, & Stahl, 2011). A drawback of the Average linkage and Weighted-Average linkage methods is that the program order within the dataset may create a bias for the group in which it is placed. To identify whether program order biases results, I will also use Ward's linkage.[6] Ward's linkage uses an analysis of variance to calculate distance. Programs are placed in a group that minimizes the sum of squared error. However, Ward's linkage does not directly consider the number of matched factors among programs. I use all three as a robustness check to demonstrate that the groupings are not contingent on using a specific clustering algorithm.

Clustering does not result in a distinct number of groups. Clustering assigns programs to groups and combines groups until all programs are merged into a single category. To identify the natural comparison group for a program, a dendrogram tree is used. Dendrogram trees illustrate the net difference in similarity calculations at the point when groups are merged. The Dendrogram trees can be used to discern when groups of non-similar programs were combined to achieve the single cluster (Everitt, Landau, Leese, & Stahl, 2011). Short (vertical) "branches" link programs with small differences, while longer lines represent a greater degree of variation (larger net difference in similarity calculations). After identifying the number of comparable groups from the dendrogram trees, the clustering algorithms can be used to list the specific programs within each "branch" of the tree.

[6] Programs are organized in the dataset based on a randomly generated number. The random number for each program was created use the random generating function in Stata. I use the random number as another method of avoiding any clustering bias based on placement in the dataset.

Residency-Based Aid Program Cluster Analysis Results

In total, 199 programs are included in the typology. The results from the cluster analysis support the assumption that residency-based programs should not be treated uniformly. The three cluster analysis methods consistently demonstrate three large constellations of programs with similar characteristics. Furthermore, each of the three cluster analysis methods is consistent with the programs that are considered comparable. The cluster analysis methods find a sharp distinction among programs that are operated by the state, programs previously described as institutional-based No Loan programs, and programs developed within the community. For this reason, I will use State-Based, Institutional, and Community-Sustained to label the three clustered groups.

Figures 1-3 illustrate the dendrogram tree for Average linkage, Weighted-Average linkage, and Ward's linkage, respectively. The bottom portion of each dendrogram tree illustrates 15 program groupings, G1-G15, that are most similar based on the program's operational procedures.[7] The three individual dendrogram trees illustrate three basic clusters of programs. Using three as the clustering number, Table 1 provides the cluster analysis results for each of the three methods. All three methods identify Institutional programs first, followed by Community-Sustained, and State-Based. The Average linkage (Figures 1) created three groups of Institutional programs (G1-3), five Community-Sustained groups (G4-8), and seven State-Based (G9-15). The Weighted-Average linkage identified the same comparable programs, but it identified six groups of Community-Sustained (G4-9) and six State-Based groups (G10-15). Ward's Linkage demonstrated a larger number of Institutional groups (G1-5), with smaller

[7] The number of programs included, 199, is too large to illustrate each program individually. The decision to divide the figure into 15 groups was made to provide the largest number of groups while maintaining legible group identifications.

groupings for Community-Sustained (G6-11) and State-Based (G12-15). The Iowa State ISU4U program is an outlier in each of the three cluster analysis approaches. The program was not placed into a group with any other programs regardless of the number of clustering method. For this reason I exclude it from the remainder of the research.

The clustering algorithm identifies groups by number. The cluster numbering is aligned with my group labels as follows: 1= State-Based, 2= Institutional, & 3= Community-Sustained. As I hypothesize, state-operated programs are separated from other programs. State policies and budgeting challenges often create the need to use criteria such as grade point average requirements, maximum income thresholds, or allowing funds to be redeemed at all public (and sometimes private) state institutions. For this reason, state level programs are included in this analysis to serve as a robustness check for the clustering process. State-based programs may have similar operational characteristics, differing only in the defined eligible geographic region. Each of the three clustering methods isolate state-based programs from programs developed within a community and institutionally funded programs.

The cluster analysis separates No Loan programs (as identified in previous research) from the residency-based aid programs derived from W.E. Upjohn and Cities of Promise. The distinction between community-supported programs and No Loan programs is less obvious. Institutional-based aid programs use a range of geographic scopes and vary in requiring secondary eligibility requirements. These are comparable to a large number of community-supported programs.

There is a strong association among the groups within the three clusters. When I force the clustering algorithms to create more than three groups, the clusters split state-based programs and No Loan programs into more-defined groups. This is evidence that the clustering algorithms view a strong distinction among the three formats of financial aid. The separation of these programs is further evidence that the growth of residency-based aid programs is unique.

Table 2 provides descriptive statistics for the three clustered groups. The numbers identify the number of programs within the specific cluster that are coded Yes (*variable*= 1) and the percentage of all programs in that cluster that this number represents. The bottom row represents the full 199 program sample statistics. The conditions used to identify early information on affordability represent a student being able to opt into or become eligible for the program prior to their freshman year in high school. This condition is present in 25% of all programs. This is far less common among State-Based programs (17%) and Institutional No loan programs (that typically require admission (1%)). Community-Sustained programs provide early information in over half, 52%, of programs.

A commitment to provide funding to eligible students is present when a program indicates that all eligible students will receive the award. A large percentage of programs abide by this type of promise, though not as many as the number of programs labeled “Promise.” A funding commitment is present in 69% of all programs. State-Based programs commit to fund all eligible students in 54% of the sample programs. Institutional No Loan programs commit to funding in 69% of the sample. Community-Sustained programs provide the largest commitment to funding, appearing in 77% of the sample.

A formula-driven percentage distribution of tuition is used in 17% of Community-Sustained programs. This is surprising given the attention generated by the Kalamazoo Promise, one of the programs that use a percent formula system. State-Based programs use a formula system in 2% of programs and no Institutional programs use this method for determining aid amount. Last-dollar aid programs cover remaining unmet need and guarantee that students can avoid out-of-pocket expenses. Within State-Based programs, 35% use last-dollar funding, as opposed to 58% of Community-Sustained programs and 97% of Institutional No Loan programs. Programs that award a single, flat aid amount are most common at the State (60%) and Community (25%) level, relative to Institutions (3%).[8]

Sub-Qualifications exist in all three clusters. State-Based requirements include grade point average and income thresholds in 50% and 56% of the programs, respectively. Institutional No Loan programs focus more on financial need (79%) than merit (10%), likely because they can uphold merit requirements through admissions. Despite the body of literature that identifies the benefits low-income students receive from Community-Sustained programs, academic merit is more frequently required (41%) than income (23%).

In total, 68% of programs provide financial aid to students, but it may only be redeemed at specified institutions. This is largely the result of Institutional No Loan programs (100%) and Community-Sustained programs (71%). Not surprisingly, State-Based aid programs rarely (17% of the time) allow aid to be used only for a specific subset of the state's public and private institutions. Aid is redeemable at two-year community colleges in 60% of the sampled programs, although this statistic is a bit misleading. State-Based (94%) and Community-Sustained programs (95%) each allow aid to be redeemed at traditionally low-cost two-year institutions. There are no programs classified as Institutional No Loan programs that can be redeemed at two-year institutions; all 72 programs limit eligibility to four-year institutions. State-based programs allow aid to be redeemed at four-year institutions across 88% of programs. Community-Sustained programs allow aid to be used at four-year institutions the least; only 47% of programs can be used directly at a four-year college.

[8] Two programs, Delaware's Inspire Scholarship and California's PACE Promise, are included in the clustering group for No Loan programs. These two programs do not provide last-dollar aid funding.

Community-Supported Residency-Based Aid Program Distinctions

Cluster analysis is used to examine the program characteristics (captured by the factor variables) to determine comparability to other programs. The end result is groups of programs that are similar overall. However, cluster analysis does not provide any evaluation of the ways that specific programs may still have small differences. As the Descriptive Statistics indicate above, programs have individual differences even within clusters. Next, I describe a method for identifying individual program comparability among the programs considered Community-Sustained residency-based aid. A similar process could be used with State-Based and Institutional No Loan programs. That is a future direction of this research.

An in-depth assessment of Community-Sustained programs is meaningful for several reasons. A detailed examination of the range of Community- Sustained program designs may be helpful to future researchers. The marginal differences across programs may have important implications to research and should be accounted for. For instance, Toutkoushian, Hossler, DesJardins, McCall, and Canche (2015) argue that residency-based aid programs that include mentoring services cannot generally be compared to programs without mentoring. The authors argue that the additional component, direct access to a network of individuals who can help students with college-going questions, acts as a second treatment (beyond the financial aid award). Consequently, the influence from financial aid cannot easily be separated from the influence created by the mentoring.

Second, the number of local communities developing residency-based aid programs continues to grow. Databases used by Perna and Leigh (2017) and Cities of Promise (2016) contain hundreds of programs currently in the developmental phases (pre-dating the official start of distributing aid awards). Policymakers and community leaders often examine existing community-supported programs during the process of developing new programs, regardless of geographic scope. For instance, community-supported programs are cited in the creation of the Tennessee Promise and the notion of nationwide “free community college” (Carruthers & Fox, 2016; Jesse, 2015; White House, 2015).

Table 3 provides a brief descriptive summary of the program specifications, by state, for the 67 programs within the Community- Sustained cluster analysis results. The 67 individual programs span 24 states and the District of Columbia. The states represented are spread out across the four Census regions of the country: Northeast (4 states), South (9 states), Midwest (5 states), and West (8 states). Michigan has the largest population of community-sponsored programs (14 programs). This is not surprising given the state’s 2008 Promise Zone legislation. Michigan added 7 of its 14 overall programs after Governor Jennifer Granholm passed the tax incentive. California (11 programs) and Illinois (6 programs) have the next-highest number of programs in the sample, followed by Arkansas and Pennsylvania (5 each).

A few general trends emerge from the descriptive statistics by state. First, programs tend to follow the same aid distribution method as other programs in the same state. Nine states have more than three Community- Sustained programs, but only Arkansas, Illinois, Michigan, and Pennsylvania have at least one program that awards a flat scholarship value, aid based on a percentage formula, and last-dollar aid awards. In particular, programs adopt structural designs similar to existing programs in the same state. This suggests either that developing programs examine the operational procedures of other programs when making structural decisions or that state-level characteristics are important considerations for community stakeholders. Second, programs that commit to provide aid to all eligible students tend to provide information on eligibility before high school. Programs making the upfront commitment to fund all students are less likely to incorporate additional qualifications that reduce the amount of outgoing aid. Lastly, despite the benefit of aiding low-income students, income qualifications are much less likely to be used by programs. Instead, programs opt to use grade point average to narrow the eligible population.

Community-Sustained Residency-Based Aid Program Spectrums

The dataset created for the clustering algorithm comprises binary variables that identify whether a program meets a specific characteristic. Clustering algorithms do not readily recognize categorical variables, so classifications must be broken into binary data points. In reality, the qualities that make up a program are more akin to a scale where characteristics can take many different forms. To categorize the areas of differentiation across the 67 Community-Sustained programs, I have established six spectrums. A spectrum is "used to classify something, or suggest that it can be classified, in terms of its position on a scale between two extreme or opposite points" (Oxford, 2016). The benefit of transforming information on program characteristics into the spectrums is primarily visual. The spectrums can be combined to demonstrate programs that are similar over multiple characteristics. This cannot be achieved with the previously described typology.

I use the basic dataset from the typology to develop the spectrums. The six main spectrums I have created are *Timeframe for Information on Commitment*, *Potential Monetary Value of Aid*, *Sub-Qualifications for Eligibility*, and *Institutional Type and Admission Requirements*. I also provide a sub-spectrum that more finely specifies the variation within the *Sub-Qualifications: Grade Point Average Requirements* spectrum. I include one additional area of operational procedure that was not included in the typology: *College Access Support Programs.* The new area does not directly relate to students obtaining early information on postsecondary affordability, but still represents differences in program design that researchers may find beneficial when examining outcomes related to early information. The spectrums are illustrated in Figures 4-9. Each spectrum identifies the range of existing alternatives and identifies the specific programs within each alternative. Next, I describe the scope of each spectrum and why the range may be relevant to future researchers.

Timeframe. Figure 4 illustrates the range of time differences for when programs provide information on eligibility. *Timeframe for Information on Commitment (Timeframe)* measures when students become aware of their eligibility or are able to finalize access into the program, if the program provides a commitment to financial aid. The *Timeframe* categories are based on the description of early information provided by previous authors and on the timing described in college choice literature. The spectrum categories are *Kindergarten through Junior High* (8^{th} grade), *High School* (9^{th} through 12^{th} grade), and *No Commitment*. Programs that provide a commitment to fund students before they enroll in high school are classified as *Kindergarten through Junior High.* The *Junior High* classification includes the stage when, according to Cabrera and LaNasa (2000), college consideration begins for students. *High School* corresponds with the point at which a student begins to establish secondary school curricular paths and postsecondary preparation (Harnisch, 2009). *No Commitment* signifies programs that do not guarantee aid to all eligible students. The time period for when students receive a commitment impacts their ability to make academic adjustments (Fryer, 2011). Additionally, the decisions made before a financial aid commitment are still relevant to the student’s opportunity costs from enrolling (Perna, 2004).

Value. Figure 5 illustrates the different values and aid distribution methods for programs. *Potential Monetary Value of Aid (Value)* is used to identify the highest amount of financial aid a student has the capability to receive and the method for determining the value of aid. The three primary types of aid distribution are flat rate, percentage-based value, and last-dollar funding. The AACC (2013) estimates that the national average tuition rate among two-year institutions is approximately $3,000. I use this value as a cut-off point for flat rate awards. The designation separates programs with a value less than or equal to $3,000 (*Flat or Capped, ≤ $3,000*) compared to programs with a specified value greater than $3,000 (*Flat or Capped, > $3,000*). The percentage-based value and last-dollar funding identify whether a formula is used for assigning a specific aid amount to each student. This includes models based on longevity and ones that cover unmet need. Prior financial aid literature indicates that the value of financial aid impacts students' postsecondary enrollment decisions (Heller, 1996; Leslie & Brinkman, 1989). For this reason, it is necessary to consider the different formats aid can take.

Sub-Qualifications**.** Figure 6 illustrates the different qualifications, beyond residency, that programs use to determine eligibility. The *Sub-Qualifications* identify additional qualifications (beyond residency) that are used to determine student eligibility for aid. The range of *Sub-Qualifications* includes programs that use *Grade Point Average (GPA)* or *Income Restrictions*, programs that use *Both* GPA and Income Restrictions, and programs that do not have any requirements beyond residency (*None*). *Income Restriction* is a dichotomous category of whether a program requires a specified Expected Family Contribution based on filing FAFSA. Residency-based aid programs may have the largest impact in creating access for low-income student populations (Blanco, 2009; Harnisch, 2009; Tierney & Venegas, 2009). Using minimum income requirements may inadvertently create an information barrier for the very group of students it is designed to capture (Doyle, 2008).

The *Sub-Qualification: GPA* includes programs that identify grade point averages starting at a 2.0 minimum GPA, 2.5 minimum GPA, and at least a 3.0 GPA (as demonstrated in Figure 7). These three grade point requirements are the most frequently used by programs, so I identify them as cut-off points. The use of a minimum GPA targets students with different levels of high school academic achievement and narrows the list of those potentially eligible (Bozick, Gonzalez, & Engberg, 2015; Gonzalez, Bozick, Taylor, & Phillips, 2011). When a program uses a GPA requirement, it may lessen the ability to forecast eligibility, even when a student is still capable of achieving the academic benchmark (Duan-Barnett, 2011).

***Institutional Type*.** Figure 8 illustrates the range of institutional choices students have for redeeming a program's aid award. The *Institutional Type and Admission Requirements* spectrum separates programs based on how aid can be redeemed at specified institutions. The spectrum identifies programs that are redeemable at any single, specific institution nationally, multiple select 2- or 4-year institutions (in-state and out of state), all 2-year institutions in the state, and all 2- and 4-year institutions in the state. Institution type restrictions influence how students respond to the creation of a program (Andrews, *et al.*, 2010; Bartik, Hershbein, & Lachowska, 2015; Bozick, Gonzalez, & Engberg, 2015; Carruthers & Fox, 2016). Limiting institutions may present additional access barriers in the form of a selective application process or "cooling out" at two-year institutions (Clark, 1964).

***College Access Support Programs*.** Figure 9 illustrates whether a support network accompanies the financial aid award and when students have access to the additional resources. The *College Access Support Programs* spectrum is divided into categories according to whether a program offers additional access to information, and if it does, when students are able to receive it: *Pre-High School, High School,* or *No Program*. Providing financial aid without supporting students through the transition may hinder a student's ability to enroll in higher education (Goldrick-Rab, 2007; Vaade, 2009; Vaade, 2010; Vaade & McCready, 2011). Support generates both social and cultural capital that can be passed between generations and student networks, and the impact can extend outside the program. The presence of *College Access Support Programs* has led to some debate over how much of postsecondary outcomes are a result of the aid award when mentoring is included (Toutkoushian, Hossler, DesJardins, McCall, & Canche, 2015).

The individual spectrums identify programs with a single similar characteristic. When used in conjunction with each other, the spectrums generate a list of programs comparable across multiple characteristics. Figures 10 and 11 provide a visual example of how the spectrums created in this typology can be used to illustrate program comparability across multiple characteristics. Here, I demonstrate the comparability of Community- Sustained residency-based programs in terms of early information on postsecondary affordability by merging *Value* and *Timeframe* (Figure 10) and *Value*, *Timeframe*, and *Sub-Qualifications* (Figure 10).

Figure 10 combines the spectrums *Timeframe* and *Value*. The *Timeframes* spectrum separates the cube vertically, with the four *Value* columns measured along the horizontal axis. Figure 10 demonstrates that the largest number of programs provide students information about affordability prior to high school by meeting unmet need. Programs that do not provide a financial aid commitment are categorized as awarding an amount that covers unmet needs, awarding less than $3,000, and awarding a value greater than $3,000.

Identifying programs that are comparable across the three spectrums is possible using a cube structure, as shown in Figure 11, which provides visual support of the how differences across the three spectrums separate programs into substantially smaller comparative groups.

Despite being considered similar in the cluster analysis, researchers may find the distinctions among the “squares” within the cube to be important. For example, the Kalamazoo Promise is located in the square with six other programs. Kalamazoo is frequently cited as the benchmark for residency-based aid programs. Beyond Kalamazoo, two other programs from Michigan are comparable: the Benton Harbor Promise and Battle Creek’s Legacy Scholars. Two programs from Illinois are comparable: Galesburg Promise and Peoria Promise. The El Dorado Promise is centered in Arkansas. The remaining 60 Community-Sustained programs have at least one difference within the three spectrums.

Figure 11 is useful for illustrating a number of blank squares and the number of squares with a high concentration of programs. For instance, there are no programs with maximum income requirements or minimum grade point average thresholds that provide students a commitment for a flat financial aid amount prior to high school. Programs that provide a flat aid amount and use sub-qualifications do not provide students with a commitment prior to high school. By comparison, Figure 11 demonstrates that a large number of programs that use a percentage formula or cover remaining unmet need give students information prior to high school (kindergarten -8th grade) and do not use sub-qualifications. The concentration of programs in the K-8th/Unmet Need/Sub-Qualifications: None square, relative to the other squares, suggests that developing programs copy the structure of existing programs. If programs developed eligibility criteria, without considering neighboring programs, we would expect a uniform spread of programs across the three-dimensional cube. If developing programs do examine the structure of their existing “neighbors”, this is further justification that a typology is needed to promote new research on student outcomes.

Discussion

This research opens several points for discussion among researchers, policymakers, and stakeholders charged with creating a commitment for financial aid to students. First, the cluster analysis results demonstrate that financial aid programs that include residency-based eligibility criteria should not be treated uniformly. As I hypothesize, Community-Sustained programs have enough differentiation in operational procedures that general comparisons with state-based programs and institutionally funded programs are unsuitable. The typology I present here focuses on the role residency-based programs play in providing students with information on postsecondary affordability.

Miller-Adams (2015) argues that all Promise programs should be treated as a single group because residency requirements and economic development constitute sufficient commonality despite the distinctions across programs. I offer this typology in opposition to this argument. The label “Promise” has been used inconsistently in both the scholarly literature and popular media. The problem is exacerbated by the frequency with which Promise appears in program titles. I find that in terms of providing information on postsecondary affordability, only a small number of programs from the large number named Promise satisfy the implication of the label − a promise to provide funding based on location. This inconsistent use of Promise in program titles can send confusing messages to students who are attempting to decipher information on postsecondary affordability.

I extend the typology to include the spectrums for Community-Sustained programs to demonstrate the variation within similarly structured programs. The cluster analysis results provide support for the hypothesis that residency-based aid programs are sufficiently different from other forms of financial aid; chiefly state-based aid programs and institutionally funded programs. The findings from the cluster analysis portion of this typology should not be taken to signify that all Community-Sustained programs are uniform. On the contrary, the spectrums demonstrate that the evolution of the grassroots Promise idea has produced a wide array of financial aid programs.

The spectrums for Community-Sustained programs provide a starting point for both qualitative and quantitative researchers to consider where potential biases may exist in their research. Quantitatively, the spectrums identify the differences in program procedure that should be accounted for when examining student outcomes. These differences may be significant in easing the transition into postsecondary education for students, or may represent additionally obstacles that mar the benefits of early information on affordability. Qualitatively, the spectrums may be a useful starting point for developing research related to student perceptions on affordability and how new information is used in the college-going decision. For instance, whether new information on Community-Sustained programs is considered trust worthier than information on other social benefit programs?

Together, the cluster analysis results and Community-Sustained program spectrums reinforce my earlier hypothesis that "Promise" programs should not be used as a uniform descriptor. The growing trend of residency-based aid programs, and the subsequent "free college" political rhetoric, are not necessarily one and the same. The details and decisions made in the developmental stage led to vast differences.

For policymakers, the typology presented here may offer a starting point for reassessing financial aid. The lack of information on affordability has prevented millions of academically qualified students from pursuing postsecondary credentials in the last decade alone, a problem labeled cost discouragement (Heller, 2006). Perna *et al.* (2008) argue that cost discouragement is not an aid availability program but rather an aid information problem. The financial aid process does not provide a commitment for funding until the point directly before enrollment; however, the structure of a program can be useful in circumventing this problem. The Congressional Budget Office (CBO, 2013) recognizes this shortcoming, noting that adjusting the criteria for federal Pell Grants to match other social welfare programs would allow students more insight in estimating their eligibility.

Residency-based aid programs have the capability to provide an efficient solution to a number of social problems, not the least of which is promoting a college-going environment. Promoting postsecondary enrollment serves to equalize social income disparities (Perna, 2004). These programs provide a cost-effective method for training the local workforce and sparking consumer spending (Andrews, 2013). Perhaps most noticeably, increasing educational attainment alters the incentives of students in ways that reduce spending on the criminal justice system and social welfare (Becker, 1964; McMahon, 2009). To maximize this level of efficiency, further research is needed on student responsiveness to specific program parameters. This typology provides a process for scholars to build upon this research.

Budgeting challenges have monopolized the headlines, as institutions try to navigate the current trend of state and federal cutbacks. One response of this may be a more in-depth assessment for efficiently allocating information to students. The continually increasing number of universally eligible scholarship programs that cite economic development as the motivating objective can be used as evidence that social returns will follow. The typology presented here is a first step in working toward this research. A similar process could be used with state-based and institutional No Loan programs. That is a future application of this research.

Paper Two: The Dell and Evelyn Carroll Scholarship

In the last decade, hundreds of communities have become more proactive in boosting postsecondary access for their residents through the development of financial aid programs. I label the financial aid format of communities fiscally supporting postsecondary access of students within a pre-defined, local region as community-sustained financial aid programs in Paper One of this dissertation. One characteristic common among a large portion of community-sustained aid programs is the commitment to provide an aid award to all students who meet the eligibility requirements. The commitment to all eligible students removes any hidden process for selectively awarding aid, and helps create transparent information on eligibility in a timeframe before the normal postsecondary financial aid process, specifically the time when students file the Free Application for Federal Student Aid (FAFSA). Early information on postsecondary affordability can stimulate college access at two-year institutions for students on the margin (Carruthers & Fox, 2016; Pluhta & Penny, 2013). Despite the growing number of community-sustained aid programs, and the percentage aligned with two-year institutions, relatively little research exists that focuses on outcomes at these institutions. This research adds to the body of literature by focusing on a community-sustained aid program that is redeemable at a single, specific two-year institution.

The Dell and Evelyn Carroll Scholarship (Carroll Scholarship, hereafter) was formally announced at a high school assembly in January 2013. The scholarship's creation came from an inheritance donation willed by the namesake couple (Harbour, 2013; Harbour, 2014). The Carroll Scholarship is last-dollar aid for all Meridian High School (Meridian) students who enroll in credit-bearing courses at the local, two-year institution Richland Community College (Richland). The last-dollar scholarship covers remaining unmet tuition and fees after all other forms of financial aid have been applied. The scholarship provides a guarantee that Meridian students will have no out-of-pocket financial obligations or require student loans to cover the cost of attendance at Richland. In the short term, the surprise announcement of the program yields an instantaneous change in student information on postsecondary affordability that can produce new incentives for the college-going decision and course-taking behaviors of eligible students.

The creation of the Carroll Scholarship generates different incentives for prior, forthcoming, and future Meridian graduates. The 2013 Meridian senior class represents the first group of students capable of using Carroll Scholarship information for their college-going decision.[9] Richland has an open-enrollment policy that does not subject students to a selective institutional admission process beyond providing proof of a high school credential. A perspective student may apply, receive admittance, and enroll in Richland courses up to the first day of the forthcoming semester. Meridian students who previously planned to forego higher education were able to use the information provided at the Carroll Scholarship announcement to reassess their college-going decision, specifically related to enrolling at Richland. Senior class members who previously opted to attend another institution could use the Carroll Scholarship information to reconsider enrolling at Richland. The surprise announcement limited the ability for 2013 Meridian senior class to adjust their college readiness with their schedule of classes, however. Students newly incentivized by the scholarship were unable to alter their academic standing and postsecondary preparation since high school course-taking choices were already established when the scholarship was announced.

[9] Educational institutions often separate student groups according to high school “senior class,” signifying their year of graduation. This is common in both secondary and postsecondary schooling. To avoid confusion in my research, the use of senior class will signify a student’s graduation year of high school.

Meridian graduates from pre-2013 senior classes also received a benefit from the scholarship announcement, as the Carroll Scholarship was created with a grandfather clause granting eligibility to all former graduates of Meridian High School.[10] Prior Meridian graduates were unable to alter their secondary school outcomes and academic preparation after the scholarship announcement, but were also unable to change their postsecondary outcomes from the semesters prior to Spring 2013 (the semester when the scholarship was announced). Prior Meridian graduates now had the ability to adjust their current and future postsecondary decisions.

Lastly, each subsequent post-2013 Meridian senior class is incentivized by the Carroll Scholarship announcement. The advanced information on eligibility for the Carroll Scholarship can be an incentive to improve secondary school academic outcomes and increase the likelihood of postsecondary success. Future graduates are able to use information on postsecondary affordability to make strategic secondary school choices related to boosting college readiness. For instance, students may elect to take secondary school courses associated with college preparation and devote additional resources to establishing study skills. Adjusting the level of college preparation reduces the trade-offs associated with postsecondary enrollment (Perna, 2004).

The combination of incentives for students from different Meridian graduating classes provides a unique environment to examine the changing student decisions and outcomes that resulted from the scholarship. This paper will use a panel dataset identified at the student-by-semester level, consisting of students who graduated from Richland's 14 in-district high schools

[10] Meridian High School was created in 1994, when the Blue Mound School District and Macon School District merged. Graduates from both high schools were eligible for the scholarship through the grandfather clause. The dataset for this research goes back to 2010, after the merger, so I will only refer to the eligible district as Meridian High School.

between 2010-2015, and who registered for credit-bearing courses at Richland. I use high school grade point average as a measure of college readiness to assess the likelihood a student was incentivized to enroll at Richland. I collapse the panel dataset to be identified at the school-by-year level to examine changes in college readiness after the Carroll Scholarship announcement. I extend the analysis into measurements of postsecondary credit-enrollment decisions, credits earned, and the cause of unearned credit hours (course withdrawal or failing semester grade). I use the student-by-semester panel dataset structure to analyze changes in student's postsecondary course-taking decisions and course outcomes, post Carroll Scholarship. Lastly, I evaluate differences in curricular decisions made by Carroll Scholarship eligible students using the collapsed school-by-year dataset. I apply a mixture of quasi-experimental Difference-in-Difference research design and multiple regression methodologies address the research questions. Formally, the three research questions are:

1.) *What differences exist in college readiness measures among Meridian graduates who enrolled at Richland after the introduction of the Dell and Evelyn Carroll community-sustained financial aid program?*
2.) *How has the Dell and Evelyn Carroll community-sustained financial aid program altered postsecondary curricular outcomes of Meridian graduates who enrolled at Richland?*
3.) *How does the Dell and Evelyn Carroll community-sustained financial aid program alter credential-seeking decisions by Meridian graduates who enrolled at Richland Community College?*

This paper is organized as follows. I begin with a brief background of Richland and its surrounding community. I review the literature of programs comparable to the Carroll Scholarship, followed by a detailed discussion of the conceptual framework and hypotheses of this research. After I describe the institutional level dataset, specifications of the Difference-in-Difference, quasi-experimental methodology, I conclude with descriptive statistics and summary of model results.

Background

Richland is located in central Illinois and primarily serves students from Macon County for which descriptive demographic data is provided in Table 4. Over the years of the study, Macon County experienced diverging income statistics within the population. Table 4 shows an increase in median household income between 2010 and 2015. The same trend holds for mean household income and per capita income, with the exception of a single year decline in 2012. Average education levels slowly increased during the years of this research. The percentage of the population (25 yrs. or older) attaining only a high school diploma decreased between 2010 and 2015, corresponding with an increased percentage of the population achieving Associate's Degrees and Bachelor's Degrees (RCC, n.d.). Despite income and educational gains, the percentage of families living in poverty changed sporadically between 2010 and 2015. In 2012, the percentage of families living in poverty (17.2%) and percentage of families living in poverty with children 18 years or younger (35.2%) each peaked (RCC, n.d.). The following year, 2013, represented the highest percentage of families with children 5 year or younger (41.3%) living in poverty (RCC, n.d.).

Changes in Macon County poverty rates follow the unemployment rate over the same time period. Table 4 shows county unemployment increasing from 2010 to 2012, where it reached 13.1% (RCC, n.d.). The rate decreased in subsequent years, likely due to the decreasing size of the civilian labor force. Table 5 provides a list of all employers with more than 100 employees. Employment in Macon County is heavily reliant on agriculture and manufacturing (RCC, n.d.).

Richland represents community college District #537, a geographic region that is made up of 14 individual high schools. The high schools include public and private, religious and nonreligious affiliations. Table 6 identifies the high schools within the research sample and the Illinois counties where the school districts reside. All 14 high schools partner with Richland to provide dual-credit course offerings. Richland reports that nearly half of dual-credit students are high school seniors and approximately 30% continue their education at Richland after graduation (RCC, 2014.). Specific to Meridian High School, dual-credit course students increased from 46 in 2009 to 119 in 2014 (RCC, 2014.).[11]

Table 7 disaggregates Richland's enrollment by in-district high school and senior class year. The table lists the number of high school graduates in each senior class, the number who enroll at Richland after graduation, and the percentage this represents of the senior class size for the 13 non-Meridian High Schools of the sample and Meridian High School. The in-district high schools not eligible for the Carroll Scholarship are recognized using a unique identifier to maintain their anonymity.[12] There is substantial variation in the senior class size of the schools within the Richland district.[13] The senior classes for several high schools exceed one hundred students each year, while the smallest senior class graduated only nine students. Meridian's senior class size fell between 73 and 79 students for each year of the study.

On average, Meridian makes up approximately 10% of Richland's in-district enrollment. The percentage of Meridian students who enroll at Richland increases by 15 percentage points in the Fall 2013 semester. After 2013, percentage of Meridian students enrolled is larger than any pre-Carroll Scholarship year. Relative to the in-district high schools, Meridian had the largest

[11] Dual credit agreements differ among the 14 in-district high schools. Some high schools cover tuition and fees for a student to take dual credit courses. The remaining schools require students to cover the cost. The Carroll Scholarship does not cover dual credit expenses.
[12] This was a stipulation made by Richland's Office of Institutional Research in exchange for obtaining access to student records.
[13] The senior class size and number enrolled at Richland are not identified for the individual schools in Table 7 because have small sample size numbers. I have made this decision because a number of schools have less than 10 students enroll at Richland and the research design used in this study does not compare Meridian to specific in-district schools.

percentage of graduating students who enrolled at Richland between 2013 and 2015. Figure 12 is a visual representation of the percentage of students who transitioned to Richland, separated by Meridian and the cumulative student population for the remaining 13 in-district schools. The figure provides visual support that the introduction of the Carroll Scholarship coincides with an enrollment boost of Meridian students at Richland and is justification that further research is necessary to identify the change in student enrollment incentives and the characteristics of students who enroll.

Literature Review

A growing body of literature examines how behaviors are modified after the announcement of a financial aid program with the characteristics similar to the Carroll Scholarship. The incentives created from these programs are not uniform; rather, they depend on program specifications. Prior research on how secondary school incentives are influenced by the announcement of a community-sustained financial aid program is examined next. After, I focus on literature specifically aligned with two-year institutions, including college access, institutional choice, and postsecondary outcomes. For a more in-depth review of community-sustained financial aid programs that include postsecondary outcomes at four-year institutions, please reference the literature review in dissertation Paper One.

Secondary School. The announcement of a community-sustained financial aid program presents new incentives for students with postsecondary aspirations, particularly underrepresented student populations (Ash, 2015; Bartik & Lachowski, 2012). Programs with non-selectivity based, transparent criteria for eligibility (for example, residency or longevity of residency) provide students upfront information on aid award and the ability to continuously monitor their own eligibility. Introducing financial incentives to students can immediately alter input driven behaviors, like time studying (Fryer, 2011; Kelchen & Goldrick-Rab, 2013). The length of time after a student learns about the financial incentive and when they earn the award is an important factor for determining how much a student is able to transform effort into outputs such as elevating their grades (Fryer, 2011). There is evidence that the announcement of a local, community-sustained financial aid program can stimulate student responses in a manner similar to secondary school financial incentives like pay-for-grades.

The Kalamazoo Promise, one of the most widely researched community-sustained programs, was announced in January 2006 and the aid was distributed quickly after (Miller-Adams, 2015). Kalamazoo awards first-dollar aid (up to 100% tuition coverage at Michigan colleges) to all eligible students, based solely on longevity of residency in Kalamazoo Public Schools (KPS).[14] Short-run Kalamazoo Promise research finds increased demand for Advanced Placement courses and decreases in the number of school suspensions (Bartik & Lachowski, 2012; Miller-Adams, 2015). The renewed sense of postsecondary access in students after the creation of the program was insufficient to transform student inputs into academic outputs for the first cohorts of Kalamazoo Promise recipients. KPS students' standardized test scores remained largely unaffected for the first three years of the program (Bartik, Eberts, & Huang, 2010). During the same three-year timeframe, average student grade point average did not statistically change either (Bartik & Lachowski, 2012; Miller-Adams, 2015).

The Kalamazoo Promise's outcomes are nearly identical to those of the El Dorado (Arkansas) Promise. The El Dorado Promise was announced in January 2007, and began distributing aid to eligible students in the forthcoming senior class (Ash & Ritter, 2014). El Dorado's program is structured similarly to Kalamazoo's, except the aid award can be redeemed

[14] I provide a detailed description on the Kalamazoo Promise eligibility criteria and aid eligibility formula in dissertation Paper One.

at any two- or four-year, public or private institution across the country. Ash and Ritter (2014) find evidence of increased test scores in math and literacy among low-income and African-American El Dorado students, however, the results are most pronounced for those who are already in the upper 50^{th} percentile. They attribute the academic gains to students in the upper 50^{th} percentile most likely having prior experience transforming input driven incentives into outcomes. The authors find no support that the scholarship announcement had a positive academic impact on students with lower likelihood to transition into postsecondary education. The El Dorado school district's implementation of a more academically rigorous curriculum, shortly after the scholarship announcement, is also attributed to lower academic outcomes. Despite the financial incentives provided by the El Dorado Promise announcement, curriculum changes lead to a reduced graduation rate among low-income students in the first cohorts of El Dorado's eligible students (Ash & Ritter, 2014).

A program with notable differences in student outcomes is Knox (TN) Achieves. The Knox Achieves scholarship (later known as tnAchieves) gave Knox County graduates full tuition coverage at any Tennessee two-year institution and required eligible students to meet with mentors during the timeframe associated with making a college-going decision. This stipulation is intended to help students overcome obstacles in the college-going process; specifically, navigating the process of transforming effort into outcomes. Carruthers and Fox (2016) attributed the program with increased high school completion rates, and with a stronger influence among female and African-American students. The authors were not able to discern how much of this influence is the result of the scholarship compared to mentoring (Carruthers & Fox, 2016).

College Access. The incentives generated by a community-sustained financial aid program are dependent on the value of the aid, and where the aid award can be carried. To date, the only research that examines a community-sustained financial aid programs impact on college access at a single, two-year institution is the three-year controlled experiment from Pluhta and Penny (2013). Pluhta and Penny (2013) examined the influence of a scholarship award based solely on high school completion. The scholarship is redeemable at a single, two-year institution for graduates of a specific low-income, inner-city school district. In the three years prior to the scholarship creation, only 6% of high school graduates applied to any type of postsecondary institution. After the implementation of the scholarship, postsecondary enrollment rose to approximately 61% of senior class members. Pluhta and Penny (2013) described the cost of operating the scholarship program as relatively low because a large portion of students qualified for financial need-based aid and did not require any funds directly from the scholarship. The authors attributed the increased college-going decision to the scholarship's commitment to fund all eligible students and the transparent eligibility criteria that was based solely on residency. The single eligibility requirement of residency left students with little doubt as to whether they would receive aid and how much out-of-pocket expense would be associated with enrollment. The scholarship did not actually create postsecondary affordability, but rather reduced perceived barriers to the specific student population. The authors also noted that a majority of students in the post-scholarship timeframe qualified for the full value of federal Pell grants indicating that most pre-scholarship students would have also likely qualified. The findings from Pluhta and Penny make a substantial contribution to financial aid research by illustrating that the early commitment from a community-based program produces a stronger signal of affordability for students than programs without a local connection.

Institutional Choice. Prior research finds that a financial aid program that stipulates the institutions or institution types that aid may be redeemed can impact the institutional choice of eligible students. For the aforementioned Kalamazoo Promise, Andrews, DesJardins and Ranchhod (2010) determined that eligible students became less likely to report ACT scores to the local, two-year institution, Kalamazoo Valley Community College (KVCC). The authors found that students simultaneously became more likely to send them to the in-state, four-year institutions Western Michigan University, Michigan State University, and University of Michigan-Ann Arbor (Andrews, *et. al*, 2010). This is telling of students institutional considerations because ACT scores can be delivered free to six different institutions, and KVCC enrolled the largest percentage of Kalamazoo Promise recipients in the years following the scholarship's announcement (Miller-Adams, 2015). Conversely, a program with a shorter, restricted list of redeemable institutions may narrow where a student considers attending. Postsecondary enrollment increases among Knox Achieves' students were concentrated at eligible two-year colleges. The two-year institution enrollment gains appear to represent students who would have enrolled at in-state, four-year institutions (Carruthers & Fox, 2016).

When aid award allows institutional choice, descriptive statistics indicate that students typically opt to attend an institution close in proximity. The nearest two- and four-year institutions to KPS enrolled the largest percentage of eligible Kalamazoo Promise students: KVCC enrolled 39% of the first class and Western Michigan University enrolled 34% of eligible students (Miller-Adams, 2015). The same two institutions have enrolled the highest percentage of Kalamazoo Promise scholars in each year since the program's announcement (Miller-Adams, 2015). Similarly, El Dorado's two-year institution, South Arkansas Community College, enrolled 29% of El Dorado Promise students in first year of the scholarship (El Dorado Promise, 2015).

Postsecondary Outcomes. Carruthers and Fox's (2016) examination of the Knox Achieves program is the only research that disaggregates the postsecondary outcomes of a community-sustained financial aid program specifically at two-year institutions. They found that the Knox Achieves program had mixed results for student's postsecondary outcomes. Scholarship recipients statistically achieve more credit hours, but demonstrate no other academic differences. The authors found no difference in grades for students who do and do not earn the award. Additionally, Carruthers and Fox (2016) found no evidence that Knox Achieves students earned college credentials at a rate different from non-eligible students.

The research I present here makes a needed contribution to the community-sustained financial aid program literature in a number of areas. In the existing research, no studies link college access, postsecondary outcomes, and curricular decisions as I do here. The dataset I have compiled for this research is a unique combination of postsecondary records (that specific includes high school transcript information) for all students who enroll at Richland, from the 14 surrounding in-district high schools (including the Carroll Scholarship eligible, Meridian High School). The dataset allows me to examine incentives from multiple perspectives. I am able to examine how the Carroll Scholarship provides different types of treatment conditions to students: early information on postsecondary affordability versus the actual scholarship value necessary to cover remaining cost of attendance. This is important for assessing how students' college-going decision was instantaneously changed as a result of the scholarship announcement, how scholarship information and actual scholarship award may produce differentiated results, and how multiple student outcomes may be impacted.

Additionally, my work provides a contribution to the field by examining a program not previously studied. There is little research focusing on the effects of a community-sustained financial aid program that is only redeemable at a single, two-year institution. This is a substantial limitation because a growing number of programs restrict enrollment to two-year institutions or a specific two-year institution. The incentives produced by the Carroll Scholarship may be unique to the programs examined in prior research. For instance, Meridian is unlike the low-income, inner-city school district with little college-going culture described in Pluhta and Penny's (2013) research. The percentage of pre-scholarship Meridian senior class members enrolling at Richland varied from 20.5% to 46.8%, compared to 6% in Pluhta and Penny's research. Additionally, on average, the Expected Family Contribution (EFC) for Meridian students is above the level for Pell Grant eligibility, demonstrating the household income difference between the programs. Therefore, my findings for Research Question #1 contribute to the literature on how middle-income students at the margin are incentivized to transition into higher education by a community-sustained financial aid program.

No research to date examines the change in student's postsecondary outcomes at a single, two-year institution after the announcement of a community-sustained financial aid program as this research does. Examining postsecondary outcomes at two-year institutions is distinct from outcomes expected from students at four-year institutions. The change in student's postsecondary outcomes is the basis for Research Question #2. Two-year institutions are more likely to capture students who previously planned to forego higher education, are the least academically prepared for higher education, and come from academically underrepresented populations (AACC, 2013).

Finally, Research Question #3 assess whether a community-sustained financial aid program influences the postsecondary curriculum a student selects to follow while enrolled at Richland. This question is missing in the current body of literature surrounding community-sustained financial aid programs. Prior financial aid research describes the presence of

Substitution Effects, which occur when financial aid programs designed to increase educational attainment inadvertently incentivize students to reduce their academic expectations (Becker, 1964; Long, 2004; Peltzman, 1973). The reduction in the cost of attendance causes students to reassess and reprioritize all forms of financial decisions, such as examining their foregone earnings differently when choosing to pursue either a terminal two-year degree or certificate. Substitution effects may also be an application of Burton Clark's (1964) "cooling out," where students at two-year institutions are redirected away from higher degree aspirations. In either case, community-sustained financial aid programs redeemable at two-year institutions may have a differentiated influence on the type of courses a student selects. This difference may be important to the communities funding these programs and warrants research.

Conceptual Framework

I use Perna's (2005) conceptual framework as a guide for student's college-going choice: a college choice conceptual framework that incorporates economic and sociological aspects into the students' decision. This conceptual framework describes four layers from which students receive information and context on postsecondary access. The layers are organized so context is funneled from the macro-environment through consecutively smaller levels representative of a student's environment and network for receiving feedback. Context is not linear or sequential so students are constantly receiving pertinent information to apply to their college-going decision. Perna (2005) states, "although college choice is ultimately based on a comparison of the benefits and costs of enrolling, assessments of the benefits and costs are shaped not only by the demand for higher education and supply of resources to pay the costs but also by an individual's habitus and, directly and indirectly, by the family, school and community context, higher education context, and social, economic, and policy context" (p. 119). Details on the application of Perna's framework to this research are covered next. Figure 13 is an illustration of the framework and includes the alignment of the covariates included in this research.

The outer layer, *Social, Economic, and Policy Context*, directly and indirectly impact a student's perception of postsecondary affordability and the opportunity costs associated with college choice. This influence occurs through federal, state, and local policy/budgets; as well as economic conditions. For example, students may receive context about the availability of state-based financial aid programs and the potential fiscal returns from entering the labor force directly (Dynarski & Scott-Clayton, 2013; Freeman, 1997; Heller, 2006; Kane, 1994; St. John & Tuttle, 2004; Zumeta, 2004). The *Higher Education Context* captures indicators students receive from institutions about admission potential, affordability, and their fit within the campus community (Adelman, 2006; College Board, 2010; Greene & Winters, 2005; Horn, Kojaku, & Carroll, 2001; Wyatt, Wiley, & Camara, 2010). *Higher Education Context* can range from generic, mass advertising to personal, direct communication/interaction between potential students and college representatives. In the *School and Community Context*, students receive feedback on college opportunities and their potential academic success from guidance counselors or other professional networks (De LaRosa, 2006; Deming & Dynarski, 2009; Freeman, 1997; McDonough & Calderone, 2006; Perna, 2005; Tierney & Venegas, 2007). In the *School and Community* context, students may begin to experience postsecondary academic expectations in the form of advanced placement courses and dual credit classes. The innermost layer, *Habitus*, embodies feedback from a student's immediate environment. In this layer, social and cultural capital provides perceptions, beliefs, and values regarding postsecondary potential (Coleman, 1988; McDonough, 1997; Perna, 2005). The feedback from the *Habitus* layer is individualized to the student based on his or her own unique circumstances.

The decision-making point in Perna's conceptual framework is similar to the Human Capital Theory and Price Theory in economics (Perna, 2004). The demand for postsecondary credentials is formed by the expected future need for higher education relative to the availability of resources to cover the cost of attendance, representing the preliminary college decision before considering the information received from the contextual layers. Feedback from the contextual layers reinforces or negates the preliminary perception of college access. Context supporting the expected benefits from receiving higher education or signals that a student will be successful in college increase the amount of education they will seek, shifting the theoretical demand for purchasing a postsecondary degree to the right. Context that diminishes the student's prior impression of higher education lowers the amount the student is willing to purchase, decreasing demand. Feedback regarding the trade-offs associated with the perceived opportunity cost of attendance also shifts demand, depending on whether the context adds to the list of sacrifices (left) or offsets the trade-offs (right). The result is the student's decision whether to enter higher education (i.e. purchase a degree).

I am applying the Carroll Scholarship announcement to two layers of context in Perna's framework. First, the announcement of the scholarship at a Meridian High School function (an all-school assembly) strengthens the perceived accessibility of Richland. Students were told that they could still pursue a college degree by enrolling at Richland, and that the scholarship guaranteed no out-of-pocket cost for attendance. The announcement also served as an advertisement of Richland's open-enrollment policy. This positively alters the level of information available to Meridian students about postsecondary access within the *School and Community Context*, relative to students from neighboring high schools.

Second, the guarantee of the scholarship provides information on postsecondary affordability to all Meridian students, in advance of filing for financial aid (for example, via FAFSA). The commitment to cover a student's remaining unmet financial need represents an increase in the supply of financial resources. Because of the Carroll Scholarship, all Meridian students have the ability to obtain 64 credit hours without relying on student loans or incurring out-of-pocket expenses for tuition and fees. The commitment from the Carroll Scholarship does not depend on individual characteristics or a selection process, providing students with greater confidence in obtaining the scholarship.

Hypotheses. Hypotheses for each of the three research questions poised in this study are presented below. The hypotheses build from the conclusions of prior research and Perna's conceptual framework, and are broken down into multiple parts as the Carroll Scholarship is likely to provide a different influence on students based on the students' previous college aspirations.

Research Question #1 asks, *what differences exist in college readiness measures among Meridian graduates who enrolled at Richland after the introduction of the Dell and Evelyn Carroll community-sustained financial aid program?* I am not able to directly observe whether a student changed their college-going decision after learning about the Carroll Scholarship, but examining college readiness measures can be used to give some insight to whether a student was likely to transition into postsecondary education. I hypothesize for Research Question #1 that the new information on postsecondary affordability will increase lead to increased levels of college readiness for Meridian students who enroll at Richland. I expect the rationale for the influence will vary based on the student's level of college readiness. Students consider prior academic achievements, like grade point average, in their assessment of the opportunity costs of enrolling in higher education.

Students who perceive they have experienced a limited amount of prior academic success believe that success in college will require higher opportunity costs (Perna, 2004); for instance, more time spent developing study skills, taking developmental course work to prepare of credit-bearing courses, and incurring the expenses of higher education with a higher risk of not completing. I believe this will explain why Meridian students in the bottom two high school grade point average quartiles, who gain new information about postsecondary affordability, will attempt to improve their level of college readiness after the scholarship announcement. I will identify this as hypothesis P2:H1a.[15] The Carroll Scholarship reduces the opportunity costs associated with enrollment by eliminating the out-of-pocket cost of attendance. Similar to the findings from other community-sustained aid programs, the reduced opportunity costs will incentivize students on the margin to enroll at the two-year institution, relative to non-eligible students (Ash & Ritter, 2014; Bartik, Eberts, & Huang, 2010; Bartik & Lachowski, 2012; Carruthers & Fox, 2016; Pluhta & Penny, 2013).

I expect that the Carroll Scholarship announcement will lead to a statistically significant increase in college readiness for Meridian students from the top two high school grade point average quartiles, that enroll at Richland, relative to non-eligible students. I expect students with higher grade point averages are likely to have devoted additional attention to academically preparing for college, to increase the chances of acceptance at their preferred institution, potentially earning merit based financial aid awards, and to increase the probability of academic

[15] The notation for hypotheses is used to help make a distinction between the research questions and three papers in this dissertation. P2 signifies the second paper of the dissertation. H1 signifies the hypothesis for Research Question #1. a. signifies the first hypothesis for Research Question #1

success. Similar to Carruthers and Fox's (2016) outcomes, a scholarship program that is redeemable at a single, two-year institution may influence students to change their institutional choice away from enrolling at a four-year institution. In this instance, the Carroll Scholarship reduces the financial opportunity costs associated with enrollment at the two-year college by providing a guarantee of tuition-free credit hours. I will refer to this as hypothesis P2:H1b.

I have provided two different explanations for the hypothesis of Research Question #1 because students may experience different types of postsecondary outcomes and curricular decisions based on their level of college readiness. Moving forward, I will refer to students from the bottom two high school grade point average quartiles, who were incentivized to transition into higher education (instead of seeking non-academic alternatives like entering the labor force), as infra-marginal students. This term is consistent with other financial aid research to identify students who were induced to attend college after a change at affordability (For example, see Dynarski, 2010). I will refer to the student population from the upper two grade point average quartiles, who are most likely to have been incentivized to enroll at Richland instead of other institutional alternatives (four-year institutions, for example), as college qualified students. I use both terms for simplicity and do not intend any other connotation.

Research Question #2 asks, *how has the Dell and Evelyn Carroll community-sustained financial aid program altered postsecondary curricular outcomes of Meridian graduates who enrolled at Richland?* Here, I assess if the Carroll Scholarship incentivizes students to alter their course registration decisions at Richland, and how course outcomes are influenced. My first hypothesis for Research Question #2 (P2:H2a) is that I expect the guaranteed zero cost of tuition will allow all Meridian students (infra-marginal and college qualified) to register for more credit hours at Richland, relative to non-eligible students. Access to a greater amount of financial resources increases student's ability to purchase additional education. This is a basic application of Price Theory and is at the core of the decision-making point of Perna's conceptual model (Perna, 2004; Perna, 2005).

In addition to the Carroll Scholarships incentives to register for more credit hours, I will also examine if there is a difference in credit hours earned and credit hours unearned for eligible students. My second hypothesis for Research Question #2 (P2:H2b) is that Meridian's infra-marginal students will not be able to transform the financial incentive to enroll at Richland into successful course completion outcomes in the short term. As a result, they will have a higher rate of failed or withdrawn credit hours relative to non-eligible students. The basis for this hypothesis is previous research on financial incentives (Fryer, 2011; Kelchen & Goldrick-Rab, 2012). The Carroll Scholarship incentivizes a student to register for additional credit hours, but does not provide academic support to increase the possibility for success.

My third hypothesis for Research Question #2 (P2:H2c) is that Meridian's college qualified students will earn a more credit hours, relative to students who are not eligible for the scholarship. Stated differently, I expect that Meridian's college qualified students will not only take additional credit hours (P2:H2a), but they will earn the credits from the additional credit hours. I expect that college qualified students are better prepared to transition into higher education, on average, and will not have the same challenges transforming input driven incentives into outcomes. This hypothesis is based on the findings from a comparable program, Knox Achieves, which incentivized students to alter their enrollment decision to a two-year institution (Carruthers & Fox, 2016).

Research Question #3 asks, *how does the Dell and Evelyn Carroll community-sustained financial aid program alter credential-seeking decisions by Meridian graduates who enrolled at*

Richland Community College? In other words, will students be more or less likely to take courses aligned with earning an Associate's Degree (the highest degree awarded at Richland, fully transferrable to other institutions). Prior research describes two dissimilar outcomes related to a student's degree progression when first enrolling in a two-year institution following high school completion.

The function of community colleges as a transition to higher-level degrees has been a point of debate over decades of research; increasingly, as a larger share of students use two-year institutions to transition into higher education. Most notably, Burton Clark (1964) describes a theory that community colleges may inadvertently guide students towards credentials beneath a Bachelor's Degree. Clark labels this "cooling out". More recently, Rouse (1995) details differing viewpoints on two-year enrollment starting with an assessment of the population of students who enroll at two-year colleges. She describes that students who opt to enroll at a two-year institution are mostly from two different groups: students who would not have normally attended higher education and students who elect to attend a two-year college instead of enrolling at a four-year institution; labeling the two potential influences of the two-year system democratization and diversion, respectively. Democratization provides a net positive effect on higher education attainment, as these students opt to gain additional education they would not previously have earned. The direction of effect for diversion is less evident. If students are able to use the credits earned at a two-year institution to better prepare them to succeed at a four-year institution, the net effect of beginning at a community college is positive. Rouse notes that some students "might be better off by starting in a four-year school where a greater fraction of the students attend full-time keeping students focused on attaining a bachelor's degree" (p. 218). Applied to this research, students who opted not to attend a four-year institution may lose focus on attaining a Bachelor's Degree and exit higher education early.

Quantitative research examining these possibilities has shown mixed results. Hilmer (1997) finds that students are able to improve their academic standing enough to gain admission to higher quality four-year institutions when starting a community college. The academic improvements are largest among students from low-income households and with lower high school academic measures. Leigh and Gill (2003) describe Rouse's democratization versus diversion in their research on community college enrollment. The authors find that students with the intent of earning a Bachelor's Degree improve their odds by selecting a community college for their transition into higher education.

In contrast, Reynolds (2012) identifies negative, significant educational attainment among students who begin at two-year institutions and expect to earn a four-year degree. Reynolds (2012) shows that the negative influence from beginning at a two-year institution may carry over into labor market returns, as well. Doyle (2009) finds that students who enroll first at a community college have a lower likelihood of completing a Bachelor's Degree. Each of the aforementioned authors references the inability to control for unobservable characteristics in their research designs, as am I.

Given the mixed results from prior research I base my hypotheses for Research Question #3 on the opportunity costs associated with following different curricular paths. I hypothesize (P2:H3a) that Meridian's infra-marginal students will be more likely to follow shorter curricular paths that align with skilled trade professions, instead of earning an Associate's Degree. Infra-marginal students likely planned to enter the labor force before learning of the Carroll Scholarship. Infra-marginal students preparation for the labor force likely included acquire the non-academic skills they would need for their chosen career field. The Carroll Scholarship represents a financial means to add to the human capital the student previously accumulated for a career in a skilled trade profession. Assuming that the student's chosen skilled trade profession does not require a college degree, I expect students will minimize their foregone earnings by selecting a non-Associates degree curricular path. For example, students may choose to earn certificates. This hypothesis is an application of Price Theory's Substitution Effect (Becker, 1964; Long, 2004; Peltzman, 1973).

For my final hypothesis (P2:H3b), I expect Meridian's college qualified students will be more likely to follow a curricular path that aligns with transferring. These students previously may have considered earning a degree beyond an Associate's Degree, but opted to enroll at Richland because of the zero cost of tuition. Richland has a large number of articulation agreements with four-year institutions within the state of Illinois, guaranteeing that all course work resulting in an Associate's Degree will be accepted as transfer credits to the four-year institution. I expect that college qualified students will use the scholarships commitment to earn the maximum amount of transferable credit hours by following an Associate's Degree curriculum or transfer curriculum. I expect that students I classified as college qualified will select this curricular path regardless of their intentions to transition into a four-year institution. I expect that they will select this path to increase their future alternatives. Specifically, by following a transferable degree path, if they opt to enroll in a four-year institution in the future, the credits they accumulate at Richland will replace credit hours that may require out-of-pocket or student loan-based financing at another institution. It is important to note that I am not testing whether a student earned a college credential, but rather how the Carroll Scholarship changed the type of courses and credential aspirations that a student sought.

Data Description

This research uses a unique student-by-semester panel dataset constructed from institutional records accumulated from different Richland departments and at different stages, including the yearly FAFSA application, Richland enrollment application form, Richland transcripts, and academic advisor notes. Data is collected for all students registered at Richland who attended one of the 14 in-district high schools and graduated between 2010-2015. The dataset consists of 1,837 Richland student semester records covering the Fall 2010 to Summer 2016 academic semesters. The 13 high schools that are not eligible for the Carroll Scholarship are de-identified within the sample for anonymity but they each have a unique, random ID to assure student alignment. All data collection was organized through Richland Community College's Office of Institutional Effectiveness and Planning, which acts as the Institutional Research office within the college.

Richland staff creates a college record for each student at the time of application and hand enters all secondary school and demographic information (age, gender, and race and ethnicity), which are self-reported by students on their enrollment application form. A high school transcript is required when a student submits their application to verify diploma receipt and courses taken.[16] The high school transcript is used to record a student's graduating high school grade point average, senior class rank, and senior class size. Richland policy is to accept partial and unofficial transcripts to speed up the enrollment process and only follows up for official transcripts when additional information is needed. High school transcripts do not capture dual credit courses. I assume that students with a Richland registration record that pre-dates their

[16] High school transcripts are frequently received as .pdf files. Richland hand enters any high school transcript information that is used to satisfy a course pre-requisite into the college's registration system by hand. The hand-entered data is made available for this research. Full copies of high school transcripts are not available.

high school graduation are dual credit courses, and I add the dual credit courses to the student's high school transcript data to reflect postsecondary exposure prior to their official transition to Richland.

Financial aid information details the students' yearly FAFSA application results, and aid awarded and distributed to students. Prior to 2015, Richland did not require students to file a FAFSA to be eligible for institutional aid, so students may have other forms of Richland financial aid without FAFSA calculations. FAFSA application however is required for students receiving the Carroll Scholarship.

Richland transcript information is separated by semester, and identifies course registration and the final course outcome: a passing letter grade (A-D), failing letter grade (F), or a Withdrawal (W). Letter grades are used to calculate college grade point average, but a W is not, although a course resulting in a W still appears on a student's Richland transcript. Students may retake any course to replace the course outcome for grade point average purposes, however all courses and outcomes remain on their transcript.

Students are asked about their academic aspirations during enrollment and advising meetings, and may choose from specific degrees, certificates, or the general transfer curriculum that contains courses articulated with other institutions. The curricular path is updated each time a student elects to make a change. Richland only keeps the most recent student response.

Treatment Conditions. Last-dollar programs structured like the Carroll Scholarship allow for multiple treatment effects. First, the scholarship provides all Meridian students with information on postsecondary affordability because each student is able to ascertain if they qualify in advance of filing for financial aid. The guarantee promoted by the program does not necessarily mean that students will require funding from the Carroll Scholarship. The information provided by the Carroll Scholarship creates two different treatment potentials. First, students who do not require Carroll Scholarship funds because the cost of attendance is ultimately covered by other forms of financial aid. A second potential treatment exists for students who either have remaining unmet need or higher Expected Family Contributions (EFC) from their FAFSA application results. The second group of students would receive Carroll Scholarship funds taking the place of paying out-of-pocket or through student loans. The two treatment variations promote different student incentives and should be examined individually.

The first type of treatment condition assessing the influence on Meridian students from receiving information on the Carroll Scholarship is represented as an interaction term of binary variables identifying whether a student is a graduate of Meridian High School (if a student graduates from Meridian High School, *Meridian*=1; if a student graduates from one of the other 13 in-district high schools, *Meridian= 0*), enrolled in 2013 or after (years 2010-2012, *Post= 0;* years 2013-2015, *Post= 1*). The primary variable of interest is the interaction term, *Meridian x Post*. The interaction term represents the Intention-to-Treat (ITT); because not all Meridian students in this model will need Carroll Scholarship funding. Instead, each Meridian student is receiving information on postsecondary affordability in the form of the guarantee of Carroll funding, if needed.

The second type of treatment condition measures the Average Treatment Effect (ATE) for Meridian students who receive Carroll Scholarship funding. I assess the effect of receiving the Carroll Scholarship using a binary and a continuous variable. I will use a binary variable for students who receive Carroll Scholarship funds (Receives scholarship, *Carroll Scholarship Recipient*= 1; Does not receive scholarship, *Carroll Scholarship Recipient*= 0). I also use a continuous variable for the value of the Carroll Scholarship funds received by a student, *Carroll*

Scholarship Amount (Receives scholarship, *Carroll Scholarship Amount*= "value"; Does not receive scholarship, *Carroll Scholarship Amount*= 0). The benefit of using *Carroll Scholarship Amount* is the ability to decipher different dosages of the treatment. I am not assuming that Carroll Scholarship recipients understand the distinction between financial aid types, rather the second treatment is being used to determine whether the additional funding from the last-dollar scholarship provides any influential effect. I will examine this second form of treatment under several different conditions related to the total cost to tuition and remaining unmet financial need.

Table 8 illustrates the breakdown of the sample student population. In total, 178 students transitioned to Richland from Meridian High School from the 2010-2015 senior classes. The grandfather clause in the Carroll Scholarship means that these students represent three groups: pre-2013 Meridian graduates who only took courses at Richland before the Carroll Scholarship (39, total), pre-2013 Meridian graduates who took courses in both pre- and post-Carroll Scholarship time periods (36, total), and Meridian students who graduated in 2013 or later only taking courses at Richland in post- Carroll Scholarship time periods (103, total).[17]

Students from the remaining 13 Richland in-district high schools are not eligible to receive the Carroll Scholarship. I describe them below in the same three time categories as Meridian students for comparison purposes only. There are 1,659 in-district students within the sample, 489 students registered only at Richland prior to 2013, 395 students registered at Richland in pre- and post-Carroll Scholarship time-periods, and 755 students graduated in 2013 or later only taking courses at Richland in post- Carroll Scholarship time periods.

[17] The dataset constructed for this research includes students who transitioned to Richland immediately following high school completion. A fourth potential group exists of students who delayed enrollment. The fourth group of students is omitted from this research.

Dependent Variables. The outcome of interest for Research Question #1 is a continuous variable of student's graduating high school grade point average (*HS GPA*). Each student has only a single measurement for *HS GPA*. For Research Question #2, the dependent variables used to measure student postsecondary outcomes are continuous variables for the number of Richland credit hours a student attempts in each academic semester (*Credit Hours: Attempted*), the number of Richland credit hours a student successfully earned in an academic semester (*Credits Hours: Earned*), how many Richland credit hours resulted in the student receiving a failing course grade during the academic semester (*Credit Hours: Failed*), and how many Richland credit hours resulted in a withdrawal during the academic semester (*Credit Hours: Withdrawn*). Lastly, the dependent variables for Research Question #3 are binary variables for *Associates Degree Path* (the student identifies a curricular path that aligns with any Associate's Degree, *Associates Degree Path= 1;* the student identifies a curricular path that does not align with any Associate's Degree, *Associates Degree Path= 0*). Richland students intending to transfer can also identify as a transfer enrollee. I assume that the decision to be a transfer enrollee aligns with earning a degree beyond an Associate's Degree, so I will examine this curricular path separately. The variable *Transferable Degree Path* is additive and includes students positively identified as *Associates Degree Path* and students selecting the transfer enrollee curriculum (the student identifies a curricular path that aligns with an Associate's Degree or the transfer enrollee status, *Transferable Degree Path= 1*; the student does not identify a curricular path that aligns with an Associate's Degree and has not selected the transfer enrollee status, *Transferable Degree Path= 0*). I include the additive *Transferable Degree Path* variable because four-year institutions do not distinguish between a non-degree-based transfer curriculum and an Associate's Degree curriculum in accepting transfer credits, per articulation agreements. This may cause students who are planning to transfer to view these two options as interchangeable, especially if a student does not intend to enroll at Richland for the number of credit hours necessary to earn an Associate's Degree. The dependent variables for Research Question #3 do not imply that a student received any form of postsecondary degree; the variables only capture the curriculum being followed by the student.

Model Covariates. Covariates are included in each model to account for variation in the dependent variable that is not associated with the treatment condition. Including covariates in regression models is important to minimize the potential of omitted variable bias (Cellini, 2008). Student race and ethnicity is a categorical variable with five predetermined options on the Richland application: White, Black or African-American, Hispanic, Two or More Races, and All Others. I use a binary variable White (if the student self-reports identifying as White, White= 1; if the student reports identifying as any other race and ethnicity, White=0) for models with low sample sizes. This is necessary because of the low percentage of Meridian students that are non-White. Dual Credit is a binary variable recognizing whether a student was previously enrolled at Richland in dual credit courses (if a student had a Richland record prior to their high school graduation date, Dual Credit Enrollee= 1; if not, Dual Credit Enrollee= 0).

To account for differences in financial resources I create a series of variables of financial aid award. Pell Grant Recipient is a binary variable determining whether the student meets federal need-based aid criteria (if student received a Pell grant award in the time period, Pell Grant Recipient= 1; if they did not, Pell Grant Recipient= 0), and Pell Grant Amount is a continuous variables for the amount awarded for Pell Grants (if the student does not receive Pell Grant, Pell Grant Amount=0). All remaining Non-Carroll Scholarship and Non-Pell Grant financial aid is captured using a continuous variable Other Aid Amount (if the student does not receive any financial aid beyond the Carroll Scholarship or Pell Grants, Other Aid Amount=0). The specific covariates used for each model will be described in the Model Specifications.

Data Limitations. Using institutional level data presents unique challenges and limitations. Institutional level data may be susceptible to errors and changes in measurement. The amount of data entered across a large number of divisions and departments within Richland increases the potential for misidentification and variation in how different characteristics are coded. For instance, I am not able to identify the specific section a student takes because of changes in how Richland codes individual courses. The data is also susceptible to human error, particularly in data entry. One such error has been found in entering the high school grade point average for incoming students. In five transcripts the *HS GPA* calculation exceeded 1,000. This is likely due to an error in entering a "0" in place of a decimal. To adjust for this, I have divided all GPA calculations that exceed 5.0 by a value of 1,000. The range of *HS GPA* after the modification was 1.085 to 5.000.

Methodology

Higher education research is susceptible to omitted variable bias and selection bias (Cellini, 2008). One method to account for the potential biases is a quasi-experimental research design. The quasi-experimental research design I use here is a Difference-in-Difference (DID) model. Angrist and Pischke (2009) described a benefit of DID is its ability to capture omitted variables at the group level. Here, those would be unobservable characteristics that led families to locate within the Meridian High School district.

A DID methodology works well for this research. Students did not have prior information about the development of the scholarship because it was organized a few months prior to the announcement (Harbour, 2013; Harbour, 2014); therefore, I am able to define the announcement date as the official start of students' receiving the treatment condition – information on postsecondary affordability at Richland. The research design and panel dataset allow me to examine how students responded, in the short term, to the surprise scholarship announcement, specifically, how students altered their college-going decision, postsecondary credit-taking behavior, and curricular decisions.

Model Specification. A recurring challenge in financial aid research is disentangling outcomes related to a program's monetary award and the psychological impact on students that occurs through signaling. A signaling influence is likely prevalent in this research. The high school assembly used to announce the Carroll Scholarship makes students aware of monetary resources, but also provides information that may be motivational to students. Information and signaling cannot completely be separated into distinct treatment conditions because each is present for all treated students. Additionally, how students conceptualize the new information and signal will be unique based on personal characteristics. While it is not possible to separate these influences it is important to use different approaches to address the biases that may present. For this reason I consider different methods for assessing the Carroll Scholarship treatment; and simultaneously acknowledge that there is no way to fully overcome this limitation. Next, I describe the models I use in this research and how I intend for them to provide different perspectives on the influence present after the Carroll Scholarship announcement.

The research questions that I pose here require the use of multiple DID models. I will first describe the general DID model followed by the specific models for the three research questions. Υ_{it} is the outcome variable for student *i* observed in a time period *t*. The coefficient for *Meridian,* β_1, identifies the average difference in outcome for students who attended Meridian High School, relative to the control group. The coefficient for *Post,* β_2, identifies the average difference in outcome for students during a time period *t,* after the Carroll Scholarship began disbursing aid. The coefficient of interest, lambda, λ, measures the average difference in outcome for student *i,* who graduated from Meridian High School in a *Post* Carroll Scholarship time period, *t*, relative to all other students. The notation lambda, λ, will be associated with the coefficient of interest in all models to maintain consistency. The general model includes a position for fixed effects, kappa, Κ. The list of relevant covariates included in the model is designated as $\mathbb{X}$ for student *i* in year *t,* and is followed by an error term. Equation 1 represents the general DID model form and the notation I will use throughout this research. Equation 1 does not contain specific model elements that are needed for this research. I present Equation 1 here only to illustrate the basic DID model format.

$$\Upsilon_{it} = \quad \beta_1\, Meridian_i + \beta_2\, Post_t + \lambda(Meridian_i\; x\; Post_t) + \mathrm{K} + \beta_3\, \mathbb{X}_{it} + \varepsilon_{it} \qquad (1)$$

The three research questions for this paper use dependent variables captured in different measures of time. The *Post* variable for each time measurement identifies when students may begin to receive the Carroll Scholarship. Research Question #1 asks about changes in *HS GPA* after the introduction of the Carroll Scholarship. This dependent variable is collected from secondary school transcripts. The time measurement for Research Question #1 is high school graduation year represented by the time subscript tau, τ. *Post* =1 when $\tau \geq 2013$. Research Question #2 records student course-taking observations and outcomes semester-by-semester. The time measurement used for semesters is sigma, ς. *Post*=1 when $\varsigma \geq 10$ (Fall Semester 2013). Lastly, Research Question #3 examines the last curricular decision made by students. The time measurement for the most recent student curricular decision is the last academic year the student registers for courses at Richland. The time measurement for academic year is rho, ρ. *Post*= 1 when $\rho \geq 2013$.

The hypotheses for Research Question #1 (P2:H1a and P2:H1b) expect the Carroll Scholarship will incentivize an increase in college readiness for infra-marginal students and college qualified students that will enroll at Richland. For this question, I collapse the student-by-semester panel dataset to aggregate to the individual high school level. This creates a high school-by-year cross-sectional dataset containing student characteristics that do not change between time periods. This is necessary because each student only has a single *HS GPA* calculation. Equation 2 demonstrates the DID model for the collapsed dataset.

$$HS\ GPA_i = \beta_1 Meridian_i + \beta_2 Post_\tau + \lambda(Meridian_i\ x\ Post_\tau) + \eta_h + \delta_\tau + \beta\ \mathbb{X}_i + \varepsilon_{ih\tau} \qquad (2)$$

Equation 2 includes high school dummy variables (η_h) to identify whether student *i* graduated from one of the 13, *h*, Non-Meridian in-district high schools. *Meridian* is a dummy variable that identifies if a student graduated from the Carroll-eligible Meridian High School. I also include year fixed effects (δ_τ) capturing the high school graduation year τ, 2010-2015. The dummy variables and fixed effects are important for accounting for variance that may result from different resources, across high schools and from year-to-year. The high school dummy variables align with the *School and Community Context* in Perna's framework. I include student characteristics ($\mathbb{X}_i$) gender and race and ethnicity to account for differences in social and cultural networks, as described by the *Habitus* layer in Perna's framework. In addition, I include Dual Credit Enrollee to capture the expected benefits and costs of enrollment from Perna's model.

Equation 2 is tested using six different populations: the full student sample, the full sample with *HS GPA* quartile dummy variables, and restricting the model to the four *HS GPA* quartiles. The *HS GPA* restricted models will identify if there is a statistical difference in grade point average unique to each of the *HS GPA* quartiles. Restricting the model is important because the two hypotheses for Research Question #1 may result in different magnitudes for the coefficient of interest. This could cause the models to appear insignificant when two significant differences exist. Figure 14 presents the quintile distribution of high school grade point average. The curve measures the total fraction of the student population (measured along the X-axis) with a high school grade point average below a specific calculation (measured along the Y-axis). Figure 14 illustrates that the *HS GPA* distribution is non-linear. A small fraction of students has a *HS GPA* below 2.0 and above 4.0. An increased enrollment of students at either end of the distribution may not be substantial to the full sample, but would represent significant population changes within the quartile. Restricting the sample by *HS GPA* quartile is important to identify and isolate the presence of incentives that create differing outcomes for students with different expectations on postsecondary enrollment. Specifically, the Carroll Scholarship may create different incentives and outcomes for Meridian's infra-marginal student population relative to the Meridian's college-qualified student population.

Research Question #2 hypotheses (P2:H2a) state that all students who receive the Carroll Scholarship will register for more credit hours than will their peers. Additionally, Meridian's infra-marginal students will be less successful in completing their credit hours (P2:H2b) at Richland, while Meridian students who are college-qualified will successfully earn a larger fraction of their credits (P2:H2c). Equation 3 illustrates an example using the dependent variable, *Credit Hours: Attempted.*

$$Credit\ Hours\ Attempted_{i\varsigma} = \lambda\left(Meridian_i\ x\ Post_\varsigma\right) + \mu_i + \theta_\varsigma + \psi_{i\varsigma} + \varepsilon_{i\varsigma} \qquad (3)$$

I include student fixed effects (μ_i) and semester fixed effects (θ_ς) to account for the *School and Community* and *Habitus* contextual layers. The notation sigma, ς, is used to distinguish the 19 semesters of the data sample. I include the vector ($\psi_{i\varsigma}$) of financial aid covariates to account for the supply of financial resources as in Perna's model: Pell Grant Recipient, Pell Grant Amount, and Other Aid Amount. The student and semester fixed effects negate the need for covariates that are unchanging within the time-periods, including *Meridian* and *Post*. Students are aligned with a single high school based on the transcript they supply to Richland; as a result, the *Meridian* variable and high school dummy variables would be perfectly identified and drop from the models. The semester fixed effect captures variance within each semester, including all semesters in the *Post* Carroll time period. This would drop *Post* from any model due to perfect identification.

The DID design and panel dataset for this research question are useful for avoiding potential contamination of the control group by Meridian students who enrolled prior to the scholarship announcement. The student-by-semester panel dataset captures student observations for each semester and applies the Carroll Scholarship at the time period the student would be eligible to receive it. Meridian students who enrolled prior to Fall 2013 begin in the control group and are switched to the treatment group in the appropriate semester. Equation 3 is tested using five different populations: the full student sample and restricting the model to the four *HS GPA* quartiles. I do not include the full sample model with *HS GPA* quartile dummy variables in these models because a student's graduating GPA does not change across postsecondary semesters. Therefore, the *HS GPA* quartile dummy variables would be perfectly identified and drop from the models. All four dependent variables (*Credit Hours: Attempted, Credit Hours: Earned, Credit Hours: Withdrawn*, and *Credit Hours: Failed*) will follow the same format.

There is a range of possible signals created from the Carroll Scholarship announcement and they are present when students make enrollment and registration decisions. The benefit students receive from the Carroll Scholarship is not solely a monetary award. Students also receive signals from the Carroll Scholarship announcement. This creates the need to consider how students may be responding differently to the actual Carroll Scholarship funding and information about Carroll Scholarship eligibility. I run a set of models designed to assess how the monetary influence and signaling influence separately from the scholarship may differ in *Credit Hours: Attempted* and *Credit Hours: Earned* using several different student populations.

First, to examine the difference of receiving funding from the Carroll Scholarship relative to Meridian students who only have Carroll Scholarship information, I examine *Carroll Scholarship Recipient* and *Carroll Scholarship Amount* treatment conditions. The treatment group for the two new conditions is Meridian students who received Carroll Scholarship funding in the specific semester. For the models examining students who receive Carroll Scholarship funds I limit the panel dataset to include only students from Meridian High School. This test is intended to identify signaling from the Carroll Scholarship. This is necessary to strictly define the control group as students with information on the Carroll Scholarship but whom did not receive funding, relative to the treatment group of students who receive funding from the Carroll Scholarship. Omitting students from the other high schools means I no longer have students who were never eligible, so I am unable to perform a DID model. Instead, I execute a set of linear models that include student covariates. This approach does not fully account for omitted variable bias, however it does make a needed contribution to the literature on how the dosage of the scholarship treatment may be influential (Bettinger, 2010). In Equation 4 I test the influence of receiving any amount of Carroll Scholarship funding, *Carroll Scholarship Recipient*.

$$Credit\ Hours\ Attempted_{i\varsigma} = \lambda\ Carroll\ Scholar.Recipient_{i\varsigma} + \theta_{\varsigma} + \psi_{i\varsigma} + \beta\ \mathbb{X}_i + \varepsilon_{i\varsigma},$$
if $MERIDIAN_i = 1$ (4)

I include semester fixed effects (θ_{ς}) and a vector for other types of financial aid, $\psi_{i\varsigma}$ (Pell Grant Recipient, Pell Grant Amount, and Other Aid Amount). I include student characteristics (represented by $\mathbb{X}_i$) White, gender, and *HS GPA* to align with Perna's *Habitus* layer. I include Dual Credit Enrollee to capture the expected benefits and costs of enrollment from Perna's model. Equation 4 is tested using six different populations: the full student sample, the full sample with *HS GPA* quartile dummy variables, and restricting the model to the four *HS GPA* quartiles. Equation 4 demonstrates the model for the *Carroll Scholarship Recipient* treatment on *Credit Hours: Attempted*. I use the same model format for the continuous treatment, *Carroll Scholarship Amount*, and using the dependent variable *Credit Hours: Earned*.

Next, I examine *Credit Hours: Attempted* and *Credit Hours: Earned* for students who are able to cover the cost of tuition using only financial aid; they do not have to pay out-of-pocket or through student loans. Unmet need is calculated using Richland's tuition rate per credit hour multiplied by the number of registered credit hours; subtracting all financial aid awarded. This calculation does not provide me with the precise cost of enrollment, as I am unable to identify additional fees that may exist for certain classes. The value only gives me an estimation of the total expense of tuition.

I limit the panel dataset to include students from all Meridian and In-District high schools that have zero unmet need based on the number of registered credit hours. I further limit the Meridian student sample to include only Meridian students who were able to cover the cost of tuition without requiring funds from the Carroll Scholarship; therefore, I am directly comparing Meridian students with no unmet need to In-District and pre-Carroll students without any unmet need. I consider unmet need because of potential biases that may be created with information on the Carroll Scholarship. When Meridian students received information on eligibility it may not have added to their perception of postsecondary affordability; particularly if they believe they would qualify for other financial aid to cover the cost of tuition. As with the previous model, this test is intended to distinguish the role of Carroll Scholarship as a signaling mechanism relative to the monetary influence. Equation 5 illustrates the model I use for tests of students with no remaining unmet need.

$$Credit\ Hours\ Attempted_{i\varsigma} = \lambda\left(Meridian_i\ x\ Post_{\varsigma}\right) + \mu_i + \theta_{\varsigma} + \psi_{i\varsigma} + \varepsilon_{i\varsigma},$$
$$\text{if } Unmet\ Need_{i\varsigma} = 0\ \&\ Carroll\ Scholar.Recipient_{i\varsigma} = 0 \qquad (5)$$

In Equation 5 I use the student-by-semester panel dataset and include student fixed effects (μ_i) and semester fixed effects (θ_{ς}). The notation is consistent with Equation 3. I include the vector ($\psi_{i\varsigma}$) of financial aid covariates: Pell Grant Recipient, Pell Grant Amount, and Other Aid Amount. Equation 5 is tested in five different populations: the full student sample and restricting the model to the four *HS GPA* quartiles.

The Carroll Scholarship is a last-dollar award and would cover the expenses of all extra courses taken, so Meridian students may choose to take courses beyond what would be covered with the other forms of financial aid. This may present a registration and credits earned bias. To examine this possibility I reassess *Credit Hours: Attempted* and *Credit Hours: Earned* for Meridian students who used the Carroll Scholarship to fill unmet need, relative to students from In-District high schools with no unmet need and pre-Carroll students who did not have access to the scholarship. I illustrate this model with Equation 6.

$$Credit\ Hours\ Attempted_{i\varsigma} = \lambda\left(Meridian_i\ x\ Post_{\varsigma}\right) + \mu_i + \theta_{\varsigma} + \psi_{i\varsigma} + \varepsilon_{i\varsigma},$$

if $Unmet\ Need_{i\varsigma} = 0$ (6)

I restrict the post-Carroll Scholarship Meridian student sample to only include students who required the Carroll Scholarship to cover the cost of tuition. The In-District and pre-2013 Meridian student population remain the same for both of the previous two models. This compares Meridian students with accept Carroll funding to cover tuition costs, to students who are ineligible for Carroll and used other forms of financial aid to cover the full cost of enrollment. The models for Equation 5 and 6 directly compare students with no out-of-pocket costs from enrollment. The differences across the two models will inform whether students view the source of financial aid differently or if the cumulative monetary value of aid is the driving influence. I use the same modeling as Equation 5.

Lastly, I restrict the model to include only students who receive Pell Grant funding. Pell Grant eligibility is not formally determined until a student completes the FAFSA application each year; however, students who qualify for free and reduced lunch in secondary school are typically also Pell qualifiers. Pell Grants are a first-dollar aid award that is applied to a student's cost of enrollment upfront. Students who qualify for full Pell Grant awards may have no remaining unmet need. Pell Grant recipients may also represent a different population because of the income requirement.

$$Credit\ Hours\ Attempted_{i\varsigma} = \lambda(Meridian_i\ x\ Post_\varsigma) + \mu_i + \theta_\varsigma + \psi_{i\varsigma} + \varepsilon_{i\varsigma},$$
$$\text{if } Unmet\ Need_{i\varsigma} = 0\ \&\ PELL_{i\varsigma} = 1\ \&\ Carroll\ Scholar.Recipient_{i\varsigma} = 0 \qquad (7)$$

I restrict the model to include just the Meridian students who are Pell Grant recipients, have no unmet need, and did not require the Carroll Scholarship to cover any remaining unmet need. I do not consider Meridian Pell Grant recipients who also receive the Carroll Scholarship because of the small sample size. I use this model to determine how students, who would likely have the cost of tuition covered using Pell Grants, receive a signal from the Carroll Scholarship announcement. Equation 7 uses the student-by-semester panel dataset with student fixed effects (μ_i) and semester fixed effects (θ_ς). I include the vector ($\psi_{i\varsigma}$) of financial aid covariates: Pell Grant Amount and Other Aid Amount, only. Equation 7 is tested in five different populations: the full student sample and restricting the model to the four *HS GPA* quartiles.

For the last research question, Research Question #3, I hypothesize that infra-marginal students who are eligible to receive the Carroll Scholarship will be less likely to follow a transferable curricular path in order to reduce the opportunity costs associated with the longer timeframe for earning an Associate's Degree (P2:H3a). I expect the coefficient of interest to have a negative sign reflecting a significant effect on students avoiding the degree path. Conversely, college qualified students who are eligible to receive the Carroll Scholarship will elect to follow a curricular path that aligns with a transferable credential, such as an Associate's Degree or transfer curriculum (P2:H3b). I expect the coefficient of interest to have a positive sign reflecting a positive effect on students selecting a transferable curricular path. I collapse the panel dataset to aggregate to the individual high school level to examine the dependent variable. This creates a high school-by-year cross-sectional dataset similar to Research Question #1 and is necessary because I am only able to identify the last curricular decision that a student makes before graduation, transferring, or no longer enrolling at Richland for any reason. The dataset is collapsed to a cross-sectional dataset using postsecondary academic year for Research Question #3. Equation 8 demonstrates the DID model for the *Associates Degree Path* dependent variable.

$$Assoc.Deg.Path_i = \beta_1 Meridian_i + \beta_2 Post_\rho + \lambda\left(Meridian_i x Post_\rho\right) + \eta_h + \delta_\rho + \beta\, \mathbb{X}_i + \varepsilon_{ih\rho} \tag{8}$$

Equation 8 includes a vector of dummy variables for the 13 Non-Meridian high schools (η_h). I include year fixed effects (δ_ρ) to capture the last postsecondary academic year a student was enrolled. The time measurement for academic year is rho, ρ. This is necessary because students could change their curricular decisions throughout their time at Richland. I assume that the decision in their last semester enrolled is the final curricular path they chose to follow. I include the student characteristic vector (represented by $\mathbb{X}_i$) with race and ethnicity, gender, and Dual Credit Enrollee. Similar to Research Question #1, *Meridian* is a dummy variable identifying if a student graduated for Meridian High School. I test this model using three different populations: the full sample population and restricting the model to two *HS GPA* quartiles, *HS GPA* quartile 1-2 and quartile 3-4. I am not able to separate these models by individual quartiles because of small sample sizes in the dependent variable. I use the same model format for the *Transferable Degree Path* treatment.

Prior Year Trends and Counterfactual Verification. One key assumption of a DID design is students from Meridian and in-district high schools behaving in similar patterns prior to the treatment being introduced. Angrist and Pischke (2009) label this the common trends assumption. The prior-year common trends assumption is necessary for assuming that post-treatment differences in outcome are attributable to being exposed to the scholarship. If the assumption of similar trends is valid, the non-eligible, in-district high school student population can be used as an acceptable proxy for the counterfactual outcomes of Meridian students who receive the Carroll Scholarship. The prior-year common trends assumption is largely untestable, however Angrist and Pischke (2009) describe that regressing the variable of interest with lag and lead covariates onto the dependent variables can be used to provide evidence that prior year trends do not exist.

One limitation of the Angrist and Pischke approach is that it cannot be used on dependent variables that maintain a single value over time periods. This limitation is pertinent because the dependent variables *HS GPA* (Research Question #1), *Associates Degree Path* (Research Question #3), and *Transferable Degree Path* (Research Question #3) have a single value for each student in my dataset. To adjust for the limitations described I will use a modification of the Angrist and Pischke approach designed to illustrate any trends in Meridian student behavior prior to receiving information on the Carroll Scholarship. The Angrist and Pischke approach is appropriate for the dependent variables for Research Question #2 (*Credit Hours: Attempted, Earned, Failed,* and *Withdrew*) because the research includes observations for Meridian student's course-taking behavior over multiple time periods. I will describe the approach I use for all three Research Questions next.

To examine whether there is a statistical difference in the *HS GPA* of Meridian students who enroll at Richland prior to the Carroll Scholarship announcement, I run linear regressions that include all students who enrolled at Richland before the Carroll Scholarship announcement was made; senior class years 2010-2012. I collapse the student-by-semester panel dataset to aggregate to the high school level creating a high school-by-year cross-sectional dataset. Collapsing the dataset is necessary because graduating students only possess a single graduating high school grade point average. *HS GPA* does not change during the postsecondary time period of this research. In the prior year trend models, I include covariates for gender, race and ethnicity, and Dual Credit Enrollee. I also include year fixed effects for the year of high school completion and Non-Meridian high school dummy variables. Additionally, I halve each of the models based on student graduating high school grade point average (*HS GPA)* allowing me to determine if there are differences among Meridian's infra-marginal (bottom two *HS GPA* quartiles) and college qualified (upper two *HS GPA* quartiles) student populations. The variable of interest in this regression is a *Meridian* High School dummy coefficient. Table 9 demonstrates that no statistical difference exists across *HS GPA* quartiles between Meridian students and students from all other non-eligible in-district high schools for any of the three dependent variables. I fail to reject the null hypothesis that the *Meridian* coefficient estimate is equal to zero. This is evidence that no enrollment trends existed for Meridian students in the years before the Carroll Scholarship announcement.

To examine prior year trends in Meridian students' *Credit Hours: Attempted, Earned, Failed*, and *Withdrew* behavior I use the approach described by Angrist and Pischke (2009). To identify if Meridian students exhibited different course-taking trends I will use interaction terms for Meridian students and all postsecondary academic years. For instance, *Meridian x 2010* will identify if there is a mean difference in the dependent variables between Meridian students in 2010 relative to the rest of sample population. *Meridian*= 1 if the student is from Meridian and *2010*= 1 if the dependent variable occurs in academic year 2010. If either indicator is untrue, the interaction term *Meridian x 2010*= 0. The interaction terms with academic years prior to 2013 serve as a falsification test of the data. If there is no difference in the years before the Carroll Scholarship announcement I will conclude that the treatment from the scholarship did not bias the control group. The models will include covariates for gender, race and ethnicity, Dual Credit Enrollee, Pell Grant Recipient, Pell Grant Amount, and the value of any Other Aid Amount. I include year fixed effects for the postsecondary academic year and a vector of Non-Meridian high school dummy variables.

Figures 15-18 display the results of these models for the dependent variables *Credit Hours: Attempted*, *Earned*, *Failed*, and *Withdrew*, separated by *HS GPA* quartile.[18] I find no evidence that Meridian students exhibited different *Credit Hours: Attempted* behaviors or experienced a statistically significant difference in *Credit Hours: Earned* in the academic years leading up to the Carroll Scholarship announcement. It is important to note that *Credit Hours: Withdrawn* (Figure 17) is significant in the 2010 academic year for Meridian's *HS GPA* quartile 4 students. Additionally, 2010 and 2012's *Credit Hours: Failed* (Figure 18) is significant for Meridian's HS GPA quartile 3 students. *Credit Hours: Withdrawn* and *Failed* are not the primary dependent variables of this research so I will elect to move forward with the analysis. The results for these variables and quartiles will be discussed in relation to the fact that they do not pass this prior year trend assessment.

Lastly, I use a similar approach for the dependent variables used for Research Question #3, *Associates Degree Path* and *Transferable Degree Path,* as I do for Research Question #1. Richland overwrites a student's curricular path with each update. This means the *Associates Degree Path* and *Transferable Degree Path* variables only identify the last choice made by students. The dataset does not allow me to assess the progression of student choices. Again, this equates to each student record containing only a single *Associates Degree Path* and *Transferable Degree Path* identifier. To identify a prior trend in curricular path I collapse the dataset to aggregate to the high school level creating a high school-by-semester cross-sectional dataset. This is similar to the explanation above for Research Question #1 with the exception that I use a postsecondary semester time period. I restrict the sample to include only students who attended Richland in the pre-Carroll Scholarship time period and identify the last semester that a student

[18] The regression tables for the *Credit Hours: Attempted, Earned, Failed,* and *Withdrew* Prior Year trend models are in Appendix D.

registered at Richland. This omits any student who registered for courses at Richland after the Carroll Scholarship announcement. As before, I split the model by *HS GPA* quartile and the variable of interest is *Meridian*. Table 10 shows the results of the models for *Associates Degree Path* and *Transferable Degree Path.* The models include covariates for gender, race and ethnicity, and Dual Credit Enrollee. Table 10 provides no evidence that there is a statistical difference in the student's curricular path, by *HS GPA* quartile, between Meridian students and students from all other non-eligible in-district high schools, in the time period before students gained information on the Carroll Scholarship.

I find from the previously described tests that Meridian students do not behave statistically different from the average Non-Meridian student in the years before the Carroll Scholarship announcement. However, the Prior Year trend assessment is not sufficient to justify whether students from the Non-Meridian high schools can be used as a counterfactual population in this research. The introduction of the Carroll Scholarship may change important demographic characteristics of Meridian students who enroll at Richland and create biased results for the coefficients of interest. Specifically, the announcement may influence the college choice decision or the income demographic for Meridian students in an unknown direction.

To assess whether there are differences in post-scholarship populations I will test for differences in the proportion of Meridian students who enroll at Richland from the four *HS GPA* quartiles and differences in the proportion of Meridian students who are Pell Grant eligible. Differences in this population will create bias results for all three research questions, because I will be capturing changes in the number of students who enroll, not just the differences in outcomes from students who would have enrolled otherwise. Stated differently, I cannot assume that Non-Meridian students remain similar to Meridian students after the Carroll Scholarship announcement.

First, I consider differences in Richland enrollment based on *HS GPA*. Figure 14 illustrates the *HS GPA* distribution for the full sample, and separated by Meridian and Non-Meridian high schools. Figure 14 demonstrates a slightly lower *HS GPA* for Meridian students; however I see that the two groups follow the same general trend in the *HS GPA* distribution. Next, I test whether being a Meridian student from a post-Carroll Scholarship senior class (2013-2015) predicts their *HS GPA* quartile placement. The variable of interest is the interaction term *Meridian x Post*. I collapse the dataset to a high school-by-year cross-sectional dataset. The models include covariates for gender, race and ethnicity, and Dual Credit Enrollee. I include senior class year fixed effects and Non-Meridian high school dummy variables. The coding and dataset transformation coincide with the description for Research Question #1 in the Model Specifications section. Table 11 shows the OLS and Logistic regression results for these models. I find no evidence that there are differences in the number of students who graduated from Meridian, in the years after the Carroll Scholarship announcement, in any of the four *HS GPA* quartiles. The coefficient of interest is not statistically significant at the 95% confidence interval for any of the models; signaling that there is no difference in the mean for Meridian and Non-Meridian students.

Second, I consider differences in Richland enrollment for Pell Grant recipient students. I use Pell Grant award as a proxy for enrollment of low-income students. Differences in income level impact the availability of other forms of financial aid and may bias results on course registration behaviors. The variable of interest is the *Meridian x Post* variable and I collapse the dataset to a high school-by-academic year cross-sectional dataset. I use academic year as the timeframe because students may only apply for federal financial aid once per year. The models include covariates for gender, race and ethnicity, Dual Credit Enrollee, HS GPA quartile dummy variables, and Non-Meridian high school dummy variables. The coding and dataset transformation coincide with the description for Research Question #3 in the Model Specifications section. Table 12 shows the OLS and Logistic regression results for whether Meridian students enrolled during the Carroll Scholarship eligible postsecondary academic years qualify for Pell Grants at statistically different rates. I find no statistical difference in the proportion of Meridian students, who are Pell Grant recipients, in the years after the Carroll Scholarship announcement.

Tables 11 and 12 provide evidence that the proportions of Meridian students, who enroll at Richland, after the Carroll Scholarship announcement, are not statistically different. There is no evidence to suggest increased proportion of Meridian students, from the infra-marginal group or the college-qualified group, enrolled at Richland. The Pell Grant findings give no indication that more or less wealthy students from Meridian enroll at Richland after the scholarship announcement. I believe that the insignificant findings, coupled with the model specifications, strongly suggest that the In-District sample population is an adequate counterfactual.

Descriptive Statistics

Student demographic information for Richland enrollees is presented in Table 7 and Tables 13-15. All tables separate statistics by high school (Meridian and in-district students), and senior class. Table 7 provides descriptive statistics on the number of students to enroll at Richland from the surrounding high schools, demographic information on RCC enrolled students, and secondary school characteristics. Richland enrollment from all in-district schools contains slightly more female than male students, ranging from 51-59%. The race and ethnicity demographic of the in-district student enrollment is approximately 80% White, falling between 79% and 82%.

Student demographics for Meridian students who enroll at Richland mirror the overall in-district demographics. The smaller Meridian senior class sizes create percentage variations that are larger than the in-district population. Meridian's student population is proportionally more female than male, with the exception of the 2015 senior class. Richland enrollees from Meridian are in excess of 90% White, with the exception of 2012 when the population was 80%. Over the six years of enrollment data, only 12 non-White students from Meridian have enrolled at Richland.

The average reported high school grade point average for in-district students is within one-eighth point in all years of study, ranging between 3.11 and 3.26. The average ACT scores among students who report their score to Richland fall between 19.23 and 20.32. ACT scores are reported to Richland for over 80% of in-district enrollees in all years. In-district students enrolling at Richland show sporadic changes in the number of secondary school mathematics courses taken in excess of graduation requirements. The number of mathematics courses taken is a signal of student postsecondary preparation (Adelman, 2006; Greene & Winters, 2005; Perna, 2004; Wiley, Wyatt, & Camara, 2010).

The average reported high school grade point average is lower and has a slightly larger range among Meridian students enrolling at Richland, as seen in Table 7, ranging from 2.70 to 2.93. The range for average ACT scores among Meridian students is also slightly larger than in-district students although it follows the same alternating trend. The number of high school courses in mathematics taken by students from Meridian trends upward starting with the 2013 senior class.

Table 13 shows financial aid outcomes for students in their first postsecondary year. I report the first postsecondary year because the number of semesters students enroll varies drastically in the study and restricting the descriptive statistics to a common timeframe is helpful for illustrating trends. The percentage of in-district students that file Free Application for Federal Student Aid (FAFSA) applications increases over the years of the study and reaches 88% in 2015. Richland's financial aid policy did not require students to file the yearly FAFSA form to be eligible for institutional aid until 2015; however, FAFSA submission was required for the Carroll Scholarship in all years after the announcement. The Expected Family Contribution (EFC) for in-district students who file FAFSA varies between $6,062 and $9,331. Student income remains within a thousand dollars in all years with a 2015 high of $2,877. Institutional grants are awarded to about one-quarter (18-28%) of entering students and range in value and funding source. This is evident by the increased average aid award in the years after the Carroll Scholarship creation. Institutional grant aid is small relative to Pell Grant awards. Pell Grant awards are distributed to between 38-49% of in-district students, in the years of the study. The percentage of eligible students slowly rises from 2012 through 2015, but average award varies significantly during that same time-period. Scholarship aid award (not including the Carroll Scholarship) is consistently between $1,312 and $1,496 in all years of the study. The highest percentage of in-district students awarded scholarships from the three years after 2013, coinciding with the introduction of the Carroll Scholarship. The percentage of tuition waiver awards and the average value increase after 2013, as well. The relationship between tuition waiver distribution and Carroll Scholarship awards may be the result of a substitution effect. Examining the impact of the Carroll Scholarship on other forms of institutional aid award is a future direction of this research. Each of the statistics described above are based on the aid categories identified by Richland's Financial Aid Department, however the college does not have an official definition for identifying aid categories.

Meridian students' financial aid outcomes are distinctly different after the 2013 Carroll announcement, demonstrated in Table 13. The percentage of Meridian students who submit FAFSA applications is at a low of 61% in 2010, but increases to 100% in 2013. The EFC and student income calculations are both higher than the in-district student population calculations. This would seem to indicate higher income levels for incoming students from Meridian, but the percentage of Meridian students who are awarded Pell grants is 53% in 2013, the highest rate among Meridian and in-district students. The percentage of Meridian students who receive scholarships and tuition waivers decreases dramatically in 2013. This could be the result of an increased number of students who do not qualify for aid or a potential substitution effect for institutionally-driven financial aid.

The percentages and values reported in Table 13 omit the Carroll Scholarship award but Table 14 provides the statistics for students who are awarded Carroll Scholarship funds. The top row of Table 14 illustrates the number of students from each senior class who received Carroll Scholarship funding and the total amount they received over all semesters after the program began distributing aid in Fall 2013. Despite the scholarship having a clause that permitted past graduate's eligibility, only a small number of students from the 2010-2012 senior classes received funding. Not surprisingly, the number of students who received Carroll Scholarship funding increases drastically starting with the 2013 senior class, as does the total amount of funding they receive in the time periods of the study. The bottom row of Table 14 illustrates the number of students who receive the Carroll Scholarship and the academic year in which they receive funding. The number of students using the scholarship in a given academic year increases from 2013 to 2015, due to the new incoming students from the most recent senior class.

First-year postsecondary outcomes are demonstrated in Table 15. I report only first postsecondary year course-taking and course outcomes because the number of semesters students enroll varies drastically in the study. The percentage of in-district students registering for 12+ credit hours in the Fall and Spring semesters (full-time status) remains close to 50% (47% to 53%). The number of registered credit hours per year is consistently between 21 and 24 during the time of the study. The number of credit hours a student successfully completes slowly increases after 2011, reaching 85.2% of credit hours resulting in a letter grade of above F. Successful course completion is the result of decreases in the number of courses failed and the number of courses a student withdraws from (or are withdrawn from).

Meridian students display multiple enrollment changes starting with the 2013 senior class. After the Carroll introduction, the number of Meridian students who register for a full-time course load jumps by 25 percentage points (40% to 65.4%). In addition to full-time enrollment, Meridian students also exhibited immediate academic results, demonstrating a 12-percentage point increase in successfully completing a course, starting with the Fall 2013 incoming student group (77% to 90%). The percent of Meridian students who failed a course decreased from 30 percent in 2010 to 7.7 percent in 2013. The academic improvements are short lived, however. In 2014, the percentage of Meridian students who fail a course increased by 35 percentage points and the number of students who withdrew from a course increased nominally (40% to 42.3%) in 2013 and by 14.5 percentage points in 2014. Meridian students do not demonstrate the same increased desire to seek Associate’s Degrees or transfer curriculum course-taking paths as their in-district counterparts in the years after 2013.

Not surprisingly, the statistics illustrated in Table 7 and Tables 13-15 demonstrate substantial variation between the in-district enrolling student population and Meridian students. This may be the result of the unexpected announcement of the program. The descriptive statistics that illustrate student decision-making offer support to the notion that the Carroll Scholarship is providing an influential effect in the short term. Variations in the average values between pre- and post-Carroll years, relative to in-district student population, are a signal that statistically significant outcomes may be present.

Results

A Difference-in-Difference quasi-experimental design was applied to identify the influence the Carroll Scholarship had on Meridian students' postsecondary college-going decisions and postsecondary course-taking outcomes. The secondary school outcome models for *HS GPA* are presented in Table 16 and postsecondary outcome models for *Credit Hours: Attempted*, *Earned*, *Withdrawn*, and *Failed* are presented in Tables 17-20, respectively. Tables 17-20 assess the influence of Carroll Scholarship information, *MERIDIAN x POST*. Tables 21-24 present results from re-evaluated dependent variables *Credit Hours: Attempted* and *Credit Hours: Earned* that contained a binary variable for receiving the Carroll Scholarship (*Carroll Scholarship Recipient*) and a continuous variable for amount of Carroll Scholarship funds received (*Carroll Scholarship Amount*) as the treatment conditions. Tables 25-30 test for differences between Meridian students who do not need the Carroll Scholarship to cover the cost of tuition, Meridian students who do use the last-dollar funding, and Meridian students who have Carroll Scholarship information and receive first-dollar Pell Grant federal aid. The identified curricular paths for students are presented in Tables 31-32, *Associates Degree Path* and *Transferable Degree Path.* All tables are organized by model numbers and identify if they contain the full sample population or are a restricted sample based on *HS GPA* quartile (Quartile 1- 4, respectively).

I use OLS regression for all models. All models contain the covariates and fixed effects described in the Model Specification section, and the results are organized by research question. The coefficients from binary treatment conditions are transformed into percentage estimates by multiplying the coefficients by 100 (such as, $\lambda \; x \; 100$). The coefficient result for the continuous treatment condition, *Carroll Scholarship Amount*, is converted to illustrate the influence for an additional $100 dollars in aid award. This approach will also be used for the coefficient results of *Pell Grant Amount* and *Other Aid Amount*. The tables reflect these alterations. I add Logistic regression results to models with binary dependent variables (*Associates Degree Path* and *Transferable Degree Path*). I do this to illustrate model robustness. The Logistic models provide estimates of the Odds Ratio (OR). ORs are non-linear estimators. All OR coefficients are positive. A coefficient greater than one is a signal that a Carroll Scholarship eligible student has greater odds of selecting a *Associates Degree Path* or *Transferable Degree Path*. Agresti (2007) notes that OLS regression provides a more intuitive interpretation of binary dependent variables; for this reason I will only interpret the OLS coefficients in the Results section.

Students in different quartiles of *HS GPA*, *Credit Hours: Attempted,* and *Credit Hours: Earned*, may experience a different impact from the Carroll Scholarship. For example, a student who enrolls at Richland part time (for instance taking a single three-credit course) may perceive eligibility from the Carroll Scholarship differently than a student who is enrolling with a full, 12 credit hours course load. If this is true, it is appropriate to include quantile regressions. Figure 19 illustrates the estimated quantile regression coefficient estimates of *Meridian x Post* for *HS GPA*, *Credit Hours: Attempted,* and *Credit Hours: Earned.* The graph charts changes in the quantile regression coefficient and the 95% confidence interval band using the model detailed in the Model Specification section. The horizontal line and confidence interval represent the OLS fixed effects regression model. The confidence interval for the quantile regression estimates fall within the OLS fixed effects regression estimates over a substantial portion of the quantiles. For this reason I opt not to run quantile regression models in addition to the models already specified. I find no compelling evidence that the quantile regression models provide a better fit than the OLS fixed effects regression models.

HS GPA. Table 16 illustrates the results for the *HS GPA* models used for Research Question #1. Model 1 shows that Meridian students from all years are likely to have a *HS GPA* lower than students from the in-district high schools. I anticipate the Carroll Scholarship will increase the enrollment of Meridian students at the lower end of high school grade point averages (P2:H1a). The increased number of Meridian students with low grade point averages will lower the mean *HS GPA* and produce a negative coefficient estimate. I find no evidence that *HS GPA* for infra-marginal students is significantly different after the introduction of the Carroll Scholarship. I also expect to find an increased number of Meridian students with high grade point averages enrolling at Richland (P2:H1b). This will increase the mean *HS GPA* and produce a positive coefficient estimate. Model 5 illustrates an increased percentage of Meridian students with *HS GPA* above 3.70 enrolled at Richland after the Carroll Scholarship announcement relative to the control group. The increased HS GPA, 0.19 ($p<0.01$), is in addition to the 0.11 ($p<0.05$) point increase among all students after 2013. Meridian students from both pre- and post-Carroll time periods have a 0.125 ($p<0.01$) lower *HS GPA* in quartile 4. In addition, Meridian students after 2013 in *HS GPA* quartile 3 have 0.05 ($p<0.01$) lower *HS GPA* after the

Carroll Scholarship announcement. All Meridian students in the *HS GPA* quartile 3 have 0.066 ($p<0.01$) lower *HS GPA*.

Postsecondary Credit Hours. Table 17 presents the results for the postsecondary student decision *Credit Hours: Attempted*. I hypothesized positive results for both infra-marginal students and college-qualified students (P2:H2a). In Model 1, I find Meridian students, after the announcement of the Carroll Scholarship, exhibit a statistically significant 1.15 ($p<0.05$) increase in registered credit hours, and I find evidence that college-qualified students are heavily influenced. After the Fall 2013 academic semester, Meridian students from the top half of the *HS GPA* distribution (quartiles 3-4) increased their registered yearly credit hours by a statistically significant 2.47 ($p<0.05$) and 3.52 ($p<0.01$), respectively. Credit bearing courses at Richland are typically either three or four credit hours. Therefore, the results for Meridian students in the *HS GPA* 4th quartile, likely represent an additional three or four credit hour course taken relative to a comparative in-district student and to Meridian student registration prior to the Carroll Scholarship. The significant results in Table 17 are in addition to the statistically significant influences for non-Carroll Scholarship financial aid and Pell Grant award amount. The value of scholarship aid not associated with the Carroll Scholarship or Pell grants, Other Aid Amount, statistically increases the number of registered credits between 0.15 ($p<0.01$) and 0.30 ($p<0.01$) for every additional $100 dollars in aid. The influence from Other Aid Amount increases with each *HS GPA* quartile. The opposite trend is true for Pell Grant aid received. Students in *HS GPA* quartile 1 increase credit hours by 0.24 ($p<0.01$), for each additional $100 received and this rate decreases with each subsequent quartile. The influence could be the result of students who do not qualify for the maximum Pell value, the opportunity costs associated with enrollment (such as foregoing work), or issues related to information on Pell eligibility, such as those described by Pluhta and Penny (2013).

Table 18 shows the results for the models of *Credit Hours: Earned*. I predict dissimilar results from students on the opposite end of the *HS GPA* quartiles. I expect Meridian's infra-marginal students will earn fewer credit hours (P2:H2b) and the college-qualified population will earn a larger number of credit hours (P2:H2c). In Model 1, I find that all post-Carroll Meridian students earned additional credit hours, a statistically significant increase of 1.87 ($p<0.01$) credit hours. The magnitude of this finding is larger than for the full model results for *Credit Hours: Attempted* (Table 17), however I failed to reject the null hypothesis that the two coefficients are statistically the same. I did find statistical significance among students from the top 2 *HS GPA* quartiles. Meridian students from *HS GPA* quartile 3 earned an additional 2.48 ($p<0.01$) credit hours, relative to a comparable student from the control group. Meridian students from the highest *HS GPA* quartile earned 3.91 ($p<0.01$) extra credit hours per semester. Placing these results in relation to *Credit Hours: Attempted*, the coefficients for *Credit Hours: Earned* are not statistically different than they were at registration. There is no evidence that Carroll-eligible students improved their academic standing. The results indicate that students successfully earn credit hours at a rate equal to the additional credit hours taken. Pell recipient students earn less credit hours, overall. The reduced credit hours are offset by the amount of Pell aid they receive. Pell recipients in all four *HS GPA* quartiles have positive rates for credit hours earned with higher award values.

I examined models for *Credit Hours: Withdrawn* and *Credit Hours: Failed* in Tables 19-20. I find that Carroll-eligible students withdraw from fewer credit hours, -0.69 ($p<0.05$), than their counterparts from the control group. This finding is concentrated among students in *HS*

GPA quartile 2 who withdraw from a statistically significant 1.50 ($p<0.05$) fewer credit hours. This equates to approximately half of a single, three credit hour course, or approximately one extra three credit hour course withdrawn from every two semesters of enrollment. In Table 20, I find evidence that Meridian students from *HS GPA* quartile 3 fail courses at a different rate after the Carroll Scholarship announcement. Carroll-eligible students fail an additional 0.65 ($p<0.01$) credit hours per semester.

Carroll Scholarship Recipient and Amount. The Carroll Scholarship provides two different forms of treatment conditions to Meridian students: a monetary aid award to be used toward the cost of tuition and a signal of postsecondary affordability. The previous models do not distinguish between the two but rather they look at the net outcome from both. Next, I run a serious of models designed to indicate whether students react differently to the Carroll Scholarship when they receive funds and whether the signal of affordability has a different, psychological impact on the enrollment decisions made by students.

In Tables 21-22, *Credit Hours: Attempted* is re-assessed using two new treatment conditions: a binary variable for receiving the Carroll Scholarship (*Carroll Scholarship Recipient*) and a continuous variable for the amount of Carroll Scholarship funding received (*Carroll Scholarship Amount*). The sample populations for Tables 21-22 were restricted to include only students from Meridian High School. The new treatment group identifies Meridian students who received Carroll Scholarship funding and the new control group represents Meridian students who did not receive the specific scholarship.

From the results in Table 21, I find that receiving any Carroll Scholarship funding statistically associated with increasing registered credit hours by 3.97 ($p<0.01$). This result is consistent across the first three *HS GPA* quartiles. Students among the low *HS GPA* group increased registered credit hours by 3.98 ($p<0.01$), students in *HS GPA* quartile 2 increased by 3.60 ($p<0.01$) and Carroll Scholarship recipients from *HS GPA* quartile 3 increased registered credits by 5.21 ($p<0.01$). The results from each quartile are statistically significant. The results likely represent that the Meridian students use the Carroll Scholarship to take an additional course per semester, after accounting for any other form of financial aid that they receive. Pell Grant Amount and Other Aid Amount also increase the number of enrolled credits.

Table 22 reinforces the prior results. I observe that students take an additional 0.365 ($p<0.01$) credit hours with each extra $100 increment of Carroll Scholarship. Similar to the results from Table 21, the trend is consistent across *HS GPA* quartiles 1-3: 0.43 ($p<0.01$), 0.31 ($p<0.01$), and 0.36 ($p<0.01$), respectively. Again, funding from the Carroll Scholarship is aligned with a statistically larger magnitude than the total value of Other Aid Amount, 0.22 ($p<0.01$) and the value of Pell Grant Amount, 0.16 ($p<0.01$).

Tables 23-24 re-assess the *Credit Hours: Earned* using Carroll Scholarship reception and the scholarships value. I find significant results that students who receive the Carroll Scholarship earn additional credit hours, presented in Table 23. Regardless of senior class year, Meridian students who receive the scholarship earn an estimated 4.38 ($p<0.01$) additional credit hours. Similar to *Credit Hours: Attempted*, the results are concentrated in the first three *HS GPA* quartiles, 4.77 ($p<0.01$), 3.99 ($p<0.01$), and 4.22 ($p<0.01$), respectively. The coefficient estimates are not statistically different than the findings from *Credit Hours: Attempted*. There is no evidence that Carroll Scholarship funding improves academic performance. The same influence is found in Table 24, which shows that each $100 of Carroll Scholarship coincides with an additional 0.42 ($p<0.01$) *Credit Hours: Earned* for Meridian students. The effect of the scholarship is centered on students in *HS GPA* quartiles 1-3: 0.53 ($p<0.01$), 0.38 ($p<0.01$), and 0.34 ($p<0.01$), respectively.

In Tables 25-30 I examine *Credit Hours: Attempted* and *Credit Hours: Earned* for all students who have the full cost of tuition covered by some form of financial aid. Tables 25-26 include Meridian students who are able to cover the cost of tuition using non-Carroll Scholarship financial aid. Tables 27-28 include only Meridian students who required the Carroll Scholarship to cover the remaining unmet need. Additionally, in Tables 29-30 I further limit the full sample population to students with no unmet need and who receive Pell Grant funding. Here, the Meridian treatment population includes only students who did not need Carroll Scholarship funding to cover the remaining cost of tuition.[19]

In Table 25, I find significant results only among students in highest HS GPA quartile. Among all students who have no remaining unmet need from course registration, Meridian students with information on Carroll Scholarship eligibility take 3.03 ($p<0.01$) credit hours. Table 26 shows that this same HS GPA quartile also earns more credit hours, 3.00 ($p<0.01$). Table 27 shows no significant results for increased credit hour taking decisions for Meridian students who use the Carroll Scholarship to cover unmet need, relative to the sample population who has no remaining unmet need. However, Table 28 illustrates that students from the lowest HS GPA quartiles statistically earn more credit hours despite the insignificant results from the course registration models. Lastly, Meridian's infra-marginal students who receive Pell Grant funding enroll in an additional 9.65 ($p<0.01$) credit hours, shown in Table 29. A larger group of Carroll Scholarship eligible students earn a statistically significant additional number of credit hours at Richland, demonstrated in Table 30. This finding supports the idea that the source of

[19] 25 Meridian students receive both Pell Grant funding and still require Carroll Scholarship funding to cover the cost of tuition. I omit these students because the sample size is too small.

funding may be irrelevant to students or that Meridian students do not opt to take extra courses just because they would be covered by the scholarship. Despite the insignificant credit taking outcomes, it appears that infra-marginal students may receive a psychologically benefit from Carroll eligibility.

Curricular Path. Tables 31-32 present the curricular path that directs the course selection of students. The models in Tables 31-32 are separated by *HS GPA* quartile 1-2 and *HS GPA* quartile 3-4. This is necessary because Logistic regression is based off the dependent variables observations equal to one (for instance, *Associates Degree Path*= 1). Separating the sample by *HS GPA* quartiles creates small sample size problems for Meridian students with either *Associates Degree Path*= 1 or *Transferable Degree Path*= 1. For this reason I combine the lower two and upper two *HS GPA* quartiles. I anticipated a reduced likelihood of Associate's degree seeking infra-marginal students (P2:H3a), and expected that this group would instead opt to follow the curricular path that ends with a certificate. I also hypothesized (P2:H3b) that college-qualified students would elect to follow the Associate's degree or transferable credential curriculum at higher rates. I find significant results for both groups of students.

In Table 31, I find that all Meridian students among the top two *HS GPA* quartiles (quartile 3-4) are more likely, 4.5% ($p<0.01$), to follow an *Associates Degree Path.* The influence of the Carroll Scholarship offsets this finding. Carroll-eligible students are 9.3% ($p<0.01$) less likely to follow an *Associates Degree Path.* Logistic regression results are significant for the corresponding models which demonstrate robust results. I do not find any results that suggest infra-marginal students are influenced toward selecting a different curricular path after the introduction of the Carroll Scholarship.

Table 32 shows the results for *Transferable Degree Path*. In this research I assume that students within from *HS GPA* quartiles (quartile 3-4), the highest-grade earners in high school, could have academically met the admission standards for four-year institutions. Students who were likely incentivized to enroll at Richland instead of a four-year university are exposed to different postsecondary credential options; specifically programs that promote a shorter, two-year curricular path and do not promote further education at a four-year institution. Consequently, students who would have elected to enroll at a four-year institution, prior to information about the Carroll Scholarship, may be altering their postsecondary expectations away from earning a Bachelor's Degree. I find that Carroll-eligible students from *HS GPA* quartile 3-4 are 7.2% ($p<0.01$) less likely to follow a *Transferable Degree Path*. The Logistic model results provide a robustness check for these findings. A *Transferable Degree Path* is defined as coursework that would be accepted by another institution toward a higher degree requirement.

This finding suggests the presence of Burton Clark's (1964) cooling out among students who are qualified to earn higher-level degrees and negative returns of Rouse's (1995) diversion. Clark states that students with greater academic capabilities, who elect to enroll at two-year institutions, first, may be inadvertently guided to exit higher education prior to earning a four-year degree. Rouse (1995) describes that students who able to use the credits earned at a two-year institution to better prepare them to succeed at a four-year institution represent a net effect of beginning at a community college. Rouse notes the alternative possibility is that some students, "might be better off by starting in a four-year school where a greater fraction of the students attend full-time keeping students focused on attaining a bachelor's degree" (p. 218).

My research does not directly assess whether a student transitions into a four-year institution; rather I consider the transferable curriculum options as an alternative to leave the possibility of transfer available to college qualified students. The estimated effects coincide with the descriptions offered by Reynolds (2012) and Doyle's (2009) research that enrolling in a two-year institution can diminish the potential for students to move forward toward a four-year degree. My findings suggest that college qualified students are less likely to use the Carroll Scholarship to earn credits that would be applicable at bachelor's degree granting institutions.

Policy Implications

This research presents a number of interesting findings in relation to community-sustained financial aid programs redeemable at single two-year institutions. The introduction of the Carroll Scholarship in January 2013 provided Meridian High School students with early information on postsecondary affordability. The model of providing financial aid based on residency is growing across the country and is becoming increasingly centered on enrollment at two-year institutions. That communities have a vested interest in addressing issues of postsecondary affordability is unsurprising given the range of theoretical economic, labor force, and societal benefits of higher education. This makes research on the Carroll Scholarship relevant to future policy creation.

Using a unique panel dataset I examine how the Carroll Scholarship alters students college-going decisions and postsecondary outcomes. I find that the scholarship incentivizes students from the highest high school grade point average quartile to enroll at Richland. This group of students is likely to have to have made the college-going decision prior to the Carroll Scholarship announcement. Information about scholarship eligibility may have altered their institutional choice to the eligible institution. The extent to which the affordability information shifted student’s enrollment decisions is untestable given this dataset.

Surprisingly, I do not find clear evidence of college access for Meridian’s infra-marginal student population. There may be a number of rationales for this. The relatively low cost of Richland means that students may not have previously felt that postsecondary access was fiscally unattainable. Stated differently, the cost of higher education is only one factor in the complex decision-making process related to postsecondary enrollment. The Carroll Scholarship reduces the out-of-pocket tuition expenses to zero; however, a number of opportunity costs associated with enrollment still exist.

The Carroll Scholarship findings present a new perspective on the role of community-sustained financial aid program’s role in promoting college access. Pluhta and Penny’s (2013) prior research describes a large increase in college-going behavior after the announcement of a similarly structured scholarship. The population sample from their research was a low-income community with a relatively low college-going rate. The same is not true of Meridian High School. Differences in the surrounding community cannot be ignored when examining student responsiveness. It can be assumed that students within Meridian High School have different levels of context regarding the postsecondary enrollment decision. This would explain variation in student responsiveness to financial aid incentives relative to other programs. The variation in responsiveness has important implications for communities reallocating resources into residency-based aid programs.

This research demonstrates that Meridian students register for a statistically significant increased number of credit hours that leads to an increased number of credits earned. This finding is on par with results from Carruthers and Fox (2016). Carruthers and Fox (2016) identify that the Knox (TN) Achieves program was influential in increasing credit hours earned after two years within higher education. These findings may be of interest to program stakeholders. The results validate that community-sustained programs can lead to improved levels of local human capital. As a growing number of programs cite both education-based and economic missions, these findings present a positive sign.

Additionally, the results indicate that students who would have been most likely to attend a four-year institution, absent the scholarship, may reduce their degree earning aspirations. The findings of this research raise questions to whether these programs are beneficial in propelling students to seek postsecondary degrees versus postsecondary certificates. This finding is substantial because the motivation for the Carroll Scholarship was to increase the number of students who could "get to their junior year of college debt-free" (Harbour, 2013).

This research has a number of future directions. This research considered the short-term impact of the scholarship announcement when Meridian students have relatively little time to adjust postsecondary preparation strategies in high school. A long-run examination of the same program will illuminate how additional years of affordability information alters students decisions on college-going and their postsecondary outcomes.

Lastly, the descriptive statistics illustrate a potential change in institutional financial aid award. The number of Carroll Scholarship eligible students who were awarded other forms of financial aid decreased after 2013, relative to the control group. Additional research is warranted to identify if the Carroll Scholarship has a financial aid spillover onto neighboring high schools reducing the out-of-pocket cost of attendance for non-eligible students.

Paper Three: The Influence of Parents' College Assets on College-going Behavior

Saving in advance of a student's postsecondary enrollment allows a family to circumvent the shock of postsecondary tuition payments by spreading the monetary sacrifice over multiple time periods. The accumulation of parents' savings decisions – hereafter parents' college assets – is becoming an increasingly important aspect of postsecondary affordability as reductions in federal and state funded financial aid are shifting a greater share of the costs of postsecondary enrollment onto students and their families (Doyle, McLendon, & Hearn, 2010; Ma, 2004). Currently, little research exists on the outcomes from households paying a larger share of the cost of postsecondary attendance. This research is a descriptive assessment of how different parents' savings strategies are correlated to the likelihood of their children attending a postsecondary institution, specifically addressing diverse student demographics and educational expectations.

Parents' college assets are comparable to an investment portfolio, where specific strategies are combined to maximize an objective, in this case college attendance of their child. Saving toward a college education however, is not fully comparable to other large-scale savings decisions, such as financially planning for retirement. The time period to accumulate postsecondary savings is less than half the typical duration for retirement. Retirement savings is often redirected from the employee's income. The savings vehicles used for retirement savings are frequently chosen from a limited number of predetermined options with different levels of identified risk. The finances and strategies to build college assets are not as straightforward.

The decision to develop college savings requires families to select and gain access to financial institutions (Doyle, McLendon, & Hearn, 2010; Ma, 2004). Next, families must make a decision on the type of financial vehicle (savings account, U.S. bonds, stock market investment, mutual funds, etc.) and consider the inherent risks associated with each vehicle. A large number of federal, state, and private education-based savings programs, such as college 529 plans or state pre-paid tuition programs, have been created in an attempt to induce families to undertake financial planning for college (Doyle, McLendon, & Hearn, 2010; Ma, 2004). The decision to use one of the education-specific programs is not straightforward. Differences across programs on cost of attendance coverage, required principal down payment, and penalties for non-qualified use complicate assessing their benefits and trade-offs (Dynarski, 2004; Hillman, Gast, and George-Jackson, 2015, Ma, 2004; Olivas, 2003). The complexity and variation of tax implications influence the decision to use these accounts but may not be fully comprehendible by families with little experience saving (Baum, 1999; Olivas, 2003). Non-education based savings vehicles such as traditional savings accounts and U.S bonds are more frequently used to save for college because of the complications associated with developing an education-based savings account (Sallie Mae, 2013).

Parents' college assets present an influence on a student's decision to enroll beyond the increased availability of monetary assets (Kim & Johnson, 2012; Scanlon & Adams, 2009; (Sherraden, 1991; Yeung & Conley, 2008; Zhan & Sherraden, 2011). Savings decisions produce a fundamentally different response from students, relative to other types of financial aid. Financial aid dollars from external entities are anonymous. Students have little or no insight on how any unused award dollars will be redirected or to whom. By contrast, students directly experience both the trade-offs associated with savings and the sacrifice by the household when parents' college assets are used. This gives students some awareness on how savings might be redirected if not spent on postsecondary expenses. Decisions made to accumulate postsecondary savings may alter students psychologically, for instance, impacting outlook and motivation

(Sherraden, 1991; Zhan & Sherraden, 2011). All else equal, the decisions made regarding postsecondary savings change the opportunity costs of enrollment for a student and may present a counterproductive influence on their college-going decision. This difference in student perceptions is not included in most research of parents' college assets.

This research fills a gap in the literature related to the strategies used by parents for saving for their student's postsecondary education and how parents' college assets align with observable students' college-going behaviors. I develop multiple strategy (treatment) groups made up of the individual decisions made by households to develop parents' college assets and describe the correlation between how student enrollment outcomes differ based on each. I employ a quasi-experimental design to account for biases in likelihood that a household saves and other characteristics that impact a student's decision to enroll. I find a correlation between the overall strategies used by families and the observed enrollment decision by the student, both for the sample population and among socioeconomic and sociodemographic sub-groups. Additionally, I find evidence that some of the individual decisions made by households to develop postsecondary savings may be leading to a counterproductive effect on observed student enrollment. The two research questions used in this work are:

1.) *What correlations exist between parents' college assets acquired by 10th grade and the observed college enrollment for different student demographics?*
2.) *How much do parents' college assets align with the observed college enrollment for different student demographics when parents identify both individual savings vehicles and household asset reallocation tactics as part of their postsecondary savings strategies*?

This paper is organized as follows. First, I describe the previous literature related to households' saving for postsecondary expenses and observed student enrollment decisions. I use this research to outline the conceptual framework and the hypotheses being applied to the research questions. Second, I provide a description of the National Center for Educational

Statistics' Education Longitudinal Study of 2002 (NCES, 2002) (hereafter, ELS:2002) dataset, the ELS:2002 survey questions regarding parents' postsecondary savings decisions, and the savings-based treatment strategies I have created from parent survey responses. Next, I describe the quantitative, quasi-experimental Propensity Score Matching methodology used to address bias in the statistical models. Finally, I provide descriptive statistics and results from the specified models. The model results are separated by treatment strategies and the individual methods corresponding with each strategy, as well as select socioeconomic and sociodemographic sub-groups.

Literature Review

Parents are present in their student's college-going decision in different capacities, including psychologically, physically, and monetarily. Parents play a pivotal role in the process of acquiring, placing context, and interpreting the value of postsecondary information (De LaRosa, 2006; Deming & Dynarski, 2009). The family's physical environment, a consequence of parent decisions, impacts the availability and accuracy of postsecondary information (Bourdieu, 1986; Coleman, 1988; McDonough, 1997; Perna, 2006). Family norms, social networks, and cultural capital shape how students personalize information and are a key component to the college choice decision (Flint, 1993; Heller, 2006; McDonough & Calderone, 2006; Perna, 2006; Tierney & Venegas, 2009).

Postsecondary Savings Decision. Decisions to save for postsecondary expenses can be thought of as a relationship between information on higher education expenses, family structure and composition, and the availability of family income and wealth. The direction of causation for these factors is not easily generalizable because the existing research surrounding parents' savings is relatively mixed. Anticipating exorbitant out-of-pocket postsecondary expenses may increase the desire to develop savings or reduce the willingness to save (Feldstein, 1995; Hossler & Vesper, 1993). Families uncertain in the ability to meet postsecondary expenses may develop savings to lessen the immediate financial impact from enrollment (Hossler & Vesper, 1993). However, limited household resources may promote the disincentive to save, a concept referred to as reverse savings (Shanks, Nicoll, & Johnson, 2014). If parents believe household savings replaces external financial aid sources they have less incentive to develop savings (Sallie Mae, 2013). Martin Feldstein (1995) equated the latter to financially savvy parents taking advantage of the financial aid system. The trade-off between savings and financial aid create the same incentives among households with a greater ability to develop savings. Families with greater access to financial resources may use the tax incentives from postsecondary savings as a wealth accumulation strategy, or they may strategically opt against savings to maximize eligibility of alternative forms of financial aid (Dynarski, 2004; Feldstein, 1995; Ma, 2004).

The decision to develop parents’ college assets is linked to household characteristics. The student’s gender and the total number of children in the family influence the decision to save (Stage & Hossler, 1989; Hossler & Vesper, 1993; Shanks, Nicoll, & Johnson, 2014). Race and ethnicity create different dynamics in the decision to develop parents’ college assets (Elliott, 2011; Elliot & Beverly, 2010; Hossler & Vesper, 1993; Stage & Hossler, 1989). African-American families are more likely to develop savings later in their child’s secondary school career (Hillman, Gast & George-Jackson, 2015). The delayed savings decision is partially a result of economic disadvantages that limit savings capability (Charles, Roscigno & Torres, 2007). Access to financial institutions to hold savings is a relevant consideration that is not uniform across all demographics. A lack of trust in financial institutions, particularly for minority populations, diminishes the desire to save (Beverly & Sherraden, 1999; Hillman, Gast & George-Jackson, 2015; Okech, Little & Shanks, 2011).

Household income is an important characteristic for postsecondary savings decisions. Current finances are the primary reason parents do not save, even when the initial deposit is $25 or less (Charles, Roscigno & Torres, 2007; Shanks, Nicoll, & Johnson, 2014). Among families that do save, household income predicts the number of savings methods used (Manly & Wells, 2009). Parents with higher levels of education and income are more likely to devote more resources towards savings, but not by reducing spending habits (Hillman, Gast & George-Jackson, 2015; Manly & Wells, 2009; Stage & Hossler, 1989). Similar to diversifying a portfolio, higher-income families use more strategies (Manly & Wells, 2009). This is not necessarily new savings. Education-related tax benefits (both state and federal) create the appearance of new savings but are most likely just resources that are relocated from different savings mechanisms (Dynarski, 2004; Ma, 2004; Olivas, 2003).

Postsecondary Savings Outcomes. The limited research on how parents' college assets promote enrollment behavior among students is mixed. Hossler and Vesper (1993) find a significant influence on enrollment overall. Their results argue that establishing parents' college asses by early high school, 9th grade is critical for influencing postsecondary enrollment. Elliott and Beverly (2010) found that neither parents' savings nor family wealth reduces the likelihood of enrollment directly after high school but the level of students' saving does. The process of maintaining and using a small funds account can signal financial management capabilities and promote enrollment (Elliott, Song, & Nam; 2013). This underscores the perception that the process for creating fiscal access can promote a psychological impact on students and influence the expectation of postsecondary attainment.

Parent savings research from Elliott (2011) uses the same ELS:2002 dataset as I use here. Elliott (2011) determines that using mutual funds provides the greatest influence for enrollment at four-year institutions.[20] My research builds upon Elliott's by making a few key deviations. I include all parent savings survey variables in the treatment conditions and consider enrollment in both two- and four-year institutions for the dependent variable. These contribute an important addition to the literature. Elliott (2011) omitted a number of survey options that are commonly used among households, such as investments in stock and real estate, sponsored college savings programs, and household sacrifices made to build savings. The omitted options account for approximately 10,000 observations in the dataset (ELS, 2002). Non-education based savings methods are the most commonly used among parents who save (Sallie Mae, 2013). By withholding these variables from the models, Elliott's results are less generalizable to the population.

I include the survey variables that identify household sacrifices to build savings. I use these variables to examine how students may be incentivized differently based on the trade-offs incurred from savings. Trade-offs are a missing aspect of the literature on parents' saving. Families make multiple decisions regarding savings vehicles and household assets when they develop their postsecondary savings portfolio; examining a single mechanism or omitting family sacrifices produces results that do not capture the full influence from savings. Lastly, I include students who enroll at two-year institutions in the models. Community colleges enroll the largest share of students who transition into higher education directly from high school (AACC, 2013). This institution type captures students on the margin, so including it in my research improves the chances of finding an enrollment influence. The growing cost of attendance in higher education

[20] Elliott (2011) interpreted the savings survey question "set up a college investment fund" as a mutual fund. In this research I include this survey question as part of the college *529 plan* individual savings vehicle.

may push a larger share of students with uncertainty in postsecondary affordability to enroll at two-year institutions.

Conceptual Framework

The literature outlined above contains important implications for this study. First, parents are essential in obtaining information on college access and interpreting the magnitude of educational returns for students. Second, factors associated with cultural, social, and human capital are important indicators for acquiring parents' college assets and describing the influence that savings has on a student's decision to enroll. A model that includes the role of parents and postsecondary finances in explaining a student's college-going decision is the conceptual framework presented by Perna (2005), an adaption of which is illustrated in Figure 20.

Perna (2005) describes a contextual progression based on information and feedback from four layers: *Social, Economic, & Policy Context*, *Higher Education Context*, *School & Community Context*, and *Habitus*. The outer two layers, *Social, Economic, & Policy Context* and *Higher Education Context* deliver public policy and economic information related to the explicit and implicit, opportunity costs of college attendance/enrollment (Dynarski & Scott-Clayton, 2013; Kane, 2003; Rodriquez, Guido-DiBirto, Torres and Talbot, 2000; Paulsen & St. John, 2002). The *School and Community Context* embodies the availability of school resources and how they steer students' consideration of postsecondary enrollment. For instance, the types of courses offered, accessibility to counselors, qualifications of teachers, and the community's engagement with academic institutions indicate postsecondary accessibility to students (De LaRosa, 2006; Perna, 2004). A family's immediate environment, *Habitus,* captures individual characteristics, perceptions, beliefs, and values. In *Habitus*, feedback and impressions from social and cultural networks help to identify how information aligns to their own unique circumstances and background (Manly & Wells, 2009; Stage & Hossler, 1989).

The contexts from these four layers are funneled into the core of the framework. Here, students use the information and context as either reaffirming or weakening their college-going consideration. A student's demand for higher education comes from the expected need for further education and the likelihood of being successful. Previous academic success, postsecondary readiness, and future employment anticipations are few examples. The context a student receives from the previous layers strengthens or diminishes how they view the returns from higher education. The supply of accessible financial resources determines the amount of education a student deems they can purchase. Accessible resources are all physical resources available to a student; for example, personal finances to cover the cost of attendance or knowledge of financial aid. The student's view of the implicit costs associated with enrollment contributes to whether a student feels the financial resources will be sufficient to meet their academic goal (i.e. a college credential). Finally, the college-going decision is made based on the interaction between a student's demand for education and the supply of available resources.

Perna (2005) describes the framework as a useful tool for assessing policy implications, specifically referencing the growing number of savings programs; but does not directly include a description of how savings fits within the framework. For this research I am applying the influence of parents' college assets to Perna's framework in two ways. The most direct application is a traditional view of how savings incentivizes enrollment. The availability of parents' college assets represents physical financial resources to cover the cost of enrollment. This aligns with the description of the supply of accessible resources in Perna's framework. All else equal, parents' college assets increase the available resources to purchase education.

Second, I apply Perna's description of the *Habitus* layer to identify how students may assess household decisions to build postsecondary savings. A student's evaluation of cultural and community beliefs influences how they view the process used to develop savings (Dynarski, 2004; Elliott, 2011; Kim & Johnson, 2012; Scanlon & Adams, 2009; Shanks, Nicoll, & Johnson, 2014). First, the process of savings may provide students with a more in-depth financial understanding and awareness. Prior research has described this a mental accounting (Elliott, 2009; Elliott, Song, & Nam, 2013). Second, a student's *Habitus* may lead to conflicting beliefs surrounding the individual household decisions made to accumulate savings. Students have insight on alternative uses for internally generated funds because they experience the sacrifices from developing this form of savings. Consequently, the opportunity cost of enrollment is not only foregone earnings, but also a student's perception of the household's trade-offs. The direction of effect on postsecondary enrollment for these two perceptions may be opposite.

Hypotheses. Building from the aforementioned framework, I have hypotheses for each of the research questions. In Research Question #1, *what correlations exist between parents' college assets acquired by 10th grade and the observed college enrollment for different student demographics?*, I expect that the cumulative savings decisions used to acquire parents' college assets will predict student enrollment into a postsecondary institution (P3:H1). This aligns with the traditional view of savings and a direct application to the core of Perna's framework. All else equal, increasing the financial resources available to a student will promote the decision to transition into higher education, relative to their matched peers. This will result in a positive coefficient for the savings methods for predicting postsecondary enrollment. I expect that this will be true for all socioeconomic and sociodemographic subgroups, including models that restrict the sample based on race and ethnicity, household income, student's expectations, and specific institution types.

In Research Question #2, *how much do parents' college assets align with the observed college enrollment for different student demographics when parents identify both individual savings vehicles and household asset reallocation tactics as part of their postsecondary savings strategies*?, I expect that educationally underrepresented student populations will respond adversely when household sacrifices are used to accumulate savings. Specifically, I hypothesize that parents' college asset portfolios identifying specific household trade-offs as a part of their strategy among the sample of non-White students, students from low-income households, and students with uncertainty in their postsecondary expectations, will predict a diminished likelihood of transitioning into higher education, relative to their matched peers. I expect that the savings vehicles used to hold savings will maintain a significant, positive coefficient on enrollment (P3:H2a), but the variables for household sacrifices will have a significant, negative coefficient (P3:H2b). Coefficients with opposite signs work to move the net effect of parents' college assets towards zero. This aligns with my second application of parents' college assets to Perna's framework: a student's evaluation of their *Habitus* and the trade-offs incurred to develop savings will increase the perceived opportunity costs of enrollment and diminish the probability of transitioning into higher education.

Data Description

Created by the U.S. Department of Education's National Center for Educational Statistics, the Education Longitudinal Study of 2002 (ELS:2002) dataset provides longitudinal information on approximately 16,200 students of the 2004 Senior Class (NCES, 2002). The data is organized as a single cohort panel dataset consisting of multiple survey sources: students, parents, and school administrators and staff. The variables used for this study originate from the 2002 base year (2002 BY) survey corresponding with the student's 10th grade year, and the second follow-up survey (2005 F2) intended to be a student's first post- high school year.

The variables of interest for this research are constructed from parents' responses to the 2002 BY survey question referencing savings specifically designated for "education after high school" (NCES, 2002). The first question in the survey sequence asks whether parents have made savings efforts for their student's education after high school and is followed by twelve survey questions identifying different savings methods and savings decisions. I examine the treatment that students receive from parents' college assets in two different ways: individual savings decisions and combined treatment strategies. I consider the subject of each of the twelve ELS:2002 parent survey questions to be an individual savings decision. The accumulation of individual savings decisions creates the combined savings strategy – a parents' college asset portfolio. Combined strategies are determined by the characteristics of all the individual treatment strategies. Table 33 identifies the specific wording for each survey question, descriptive statistics on the number of households that positively identified using each individual savings decision, and how I align each savings decision with a combined savings strategy.

Each survey question presented parents multiple options for answering, including "Yes," "No," and several reasons why the question could not be answered.[21] I transform the survey responses into binary variables where Yes = 1 if the parent identified using that method/decision for savings and No= 0 if the parent identified they did not use that method. I use three different procedures for coding missing answers. If a parent identified that they did not have savings

[21] For instance, a survey question was considered a legitimate skip if the parents had already answered that they did not have savings efforts for 10th grader's education after high school of if parents did not aspire for their child to attend a postsecondary institution.

efforts for education after high school and skipped the twelve individual questions (considered a legitimate skip in the ELS:2002 codebook), I coded “No” for all individual methods. If a parent identified “Yes” for any of the individual options, I assumed all skipped questions represented a “No” response. Lastly, I omitted a student from the sample if all questions related to savings were skipped. This was necessary because there is no method to identify if a student should be included in the treatment or control group.

Treatment Conditions. Most studies that examine the relationship between parents’ savings and student enrollment behavior omit certain forms of savings or consider savings as a dichotomous treatment with a single effect. This contributes to a general understanding of parents’ savings, but it does not adequately address whether various components of the savings strategy have differential, and potentially confounding, influences. One strength of this study is the assessment of how the full combination of savings strategies influences the likelihood of enrollment, and the influence of the individual decisions present within parents’ college asset portfolio.

The wording of the twelve individual 2002 BY survey questions suggests a natural separation into three overarching areas for developing a postsecondary savings strategy. Prior savings research (Sherraden, 1991; Yeung & Conley, 2008; Zhan & Sherraden, 2011) identifies that student’s may have different perceptions of savings depending on the type of asset. Specifically, Sherraden (Sherraden, 1991; Zhan & Sherraden, 2011) look at the distinction between financial and non-financial assets. Financial assets are described as easily liquidated, “ready-to-use” (Zhan & Sherraden, 2011, p. 847) to help smooth economic stress. The examples provided of Non-financial assets liabilities include debt related assets, such as homeownership. Similarly, Orr (2013) discusses that student’s may have a different perception of household savings based on how the asset is held. Orr (2013) uses the descriptors Liquid and Non-Liquid. I use the general description for savings methods as the bases for creating the treatment categories from the survey questions.

I interpret the survey questions starting with *Started, Bought, Established, Made, Participated,* and *Set up* as verbs and the subject of the survey question as the vehicle used to hold savings. This most closely coincides to the idea of financial assets presented by Zhan and Sherraden (2011). I include the decisions using verbs *Remortgaged*, *Reduced*, and *Working* in a separate category. I treat the methods associated with these verbs as the Non-Financial, Non-Liquid group. Lastly, I assume that the verb *Planned* indicates methods intended as a future action to be used after the 2002 BY survey. I am unable to determine if households took these actions after the survey date. A large number of families identify these intentions in their survey responses so I opt to include this as a separate category. I identify the three different categories that parents have used to develop savings as past tense actions made to develop a method to holding savings, past tense actions used to accumulate savings value, and future intentions for actions to accumulate savings and value. Next I describe the three treatment groups I have created using the survey question responses.

The survey questions that I consider past financial actions made holding savings are positive responses to whether a parent started a savings account (*Savings*), bought an insurance policy (*Insurance*), bought U.S. savings bonds (*U.S. Bonds*), established another form of savings (*Other Savings*), made an investment in stocks/real estate (*Stocks/Real Estate*), participated in state-sponsored college savings program (*529 plan*), and/or set up a college investment fund (*529 plan*). Using a general savings account, *Savings*, is the most popular method identified by parent responses. A general savings account is included in the parents' college asset portfolio of 78% of households that save. Savings accounts are traditionally a risk-free vehicle for savings. Insurance policies (*Insurance*) are frequently associated with longer-term, risk-free savings that allow multiple withdrawal provisions such as life, health, and education (Williams, 2015). Purchasing U.S. savings bonds (*U.S. Bonds*) is another risk-free form of savings that matures based on the specific bond rate and maturation date. Investing in real estate or the stock market (*Stock/Real Estate*) is likely a risky form of savings but with the potential for high returns. The alternative savings method (*Other Savings*) asks if parents established another form of savings. No further description is available about this survey option. The survey questions that inquire to whether a parent set up a college investment fund or participated in state-sponsored college savings programs, are worded to imply a college targeted savings method (*529 plan*). College specific plans typically have intricate tax and tuition coverage policies, with variation in withdrawal eligibility. ELS:2002 does not provide additional insight on the distinctions between these two mechanisms so I combine them to represent savings vehicles designed specifically for postsecondary use.

The first combined savings treatment I create for this research is labeled *Past Account Creation*. I classify households as having a *Past Account Creation* strategy for parents' college assets if they only selected at least one option from: *Savings*, *Insurance*, *U.S. Bonds*, *Other Savings*, *Stocks/Real Estate*, or *529 plans*. Conceptually, this is the most basic idea of what savings represents: a family depositing capital into an account. The savings amount increases through additional deposits and the incurred return on investment. In the ELS:2002 dataset, families falling within the *Past Account Creation* combined strategy use an average of 2.85 different vehicles to make up their savings portfolio.

The second grouping of savings strategies I term *Past Asset Reallocation*. This category identifies how household assets were previously redirected to accrue college savings. This strategy includes all the survey questions that were not readily liquid, increase liability, or could be considered non-financial in nature. The survey questions aligning with this category are: remortgaged property/took out a home-equity loan (*Remortgaged*), reduced other expenses in some way (*Reduce Expense*), and started working another job/more hours (*Add Job*). The *Past Asset Reallocation* category provides insight to the sacrifices that each family is making to accrue savings and represents the physical decisions that are most observable to students or that would impact the student's immediate environment. These sacrifices may alter the postsecondary expectations or the perception students have of postsecondary affordability. Students may view this type of savings strategy differently based on their *Habitus* (Perna, 2005). I am not assuming that each of these options is equally visible to students, that parents have discussed them with their student, or that the student is capable of comprehending the decision. Instead, this group of savings strategies consists of decisions made by parents that will impose an influence on the student's environment. Families in both the *Past Account Creation* and *Past Asset Reallocation* groupings have an average of 4.18 different individual methods/decisions represented in their parents' college asset portfolio.

Future Intentions is the final grouping, which indicates whether families have chosen to either continue or add a strategy after the 2002 BY survey. The survey questions for this group are: planned to reduce other expenses in some way (*Plan to Reduce Expenses*) and planned to remortgage property/take out a home-equity loan (*Plan to Remortgage*). An average of 4.37 different mechanisms are used among households whose survey responses are positive for all three approaches: *Past Account Creation, Past Asset Reallocation* and *Future Intentions.*

Dependent Variables. The dependent variable for this analysis distinguishes whether an individual student enrolled into a postsecondary institution immediately following high school graduation. *Enrollment* is a binary variable (Yes= 1) collected from the 2005 follow-up (F2) student survey. This corresponds with the year a student would be a college freshman if they completed high school in the two years following their 10th grade year. Unlike previous research, the measure for enrollment does not require enrollment into a four-year institution. *Enrollment* may be at a public or private college, as well as two- or four-year institutions. This is an important contribution of this study, since a growing share of all students is deciding to attend two-year institutions. Omitting this institution type has been a substantial limitation in prior literature (AACC, 2013).

Data Limitations. Using a pre-existing dataset has limitations, the most notable is that I am not able to identify specific savings programs. For instance, the Coverdell Education Savings Account and 529 Savings Plans are both generally considered savings mechanisms for postsecondary financing, but they are not separately identified in the ELS:2002 survey. As a result, I use a single, combined measure (*529 plan*).

In the ELS:2002 dataset, a substantial number of parents (3,000) do not respond to any of the savings-based survey questions. These students are omitted from this research due to missing values. An unobserved bias may be present with these families. This bias does not appear to be related to college enrollment as 66% of the omitted sample entered college after completing high school, as compared to 77% in the total sample. Nonetheless, the results of this research only apply to the usable sub-sample.

Any students who drop out of high school prior to receiving a diploma or who were required to repeat a grade between 10th and 12th are omitted from this research. These students may eventually experience an effect from parental savings towards college enrollment, but this would not be observed in the ELS:2002 follow-up survey. This narrows the usable sample to students who are academically and socially able to complete the final three years of high school uninterrupted.

A different limitation exists that is data-driven and conceptual in nature. The rising cost of postsecondary tuition is among the reasons identified for increased household savings. Unfortunately, this does not address a household's belief for how much savings is needed. A limitation in the data is the inability to identify how much savings family's intent to accrue for college expenses, or an insight into how much they think will be necessary. The expected cost of higher education is likely one driver for the individual decisions on postsecondary savings; failing to account for this in the models creates an unknown bias. One way to lessen this potential bias is with information on the price of tuition at the institution a student first enrolled in. This information can be determined through the restricted access ELS:2002 dataset. Using this data is a future direction of this research.

Methodology

Higher education research intending to identify a causal effect on postsecondary outcomes is subject to omitted variable and selection bias (Cellini, 2008). Quasi-experimental design methods offer an appropriate solution to address these biases. The quasi-experimental research design used here is Propensity-Score Matching (PSM). Specific to this research, PSM uses relevant factors identified from prior literature to create an estimate that parents would establish college savings prior to their student entering 10^{th} grade. The matching process aligns students from the treatment group, students with parents' college assets, to students from the control group, *Non-Intent*.

The control group of this study, *Non-Intent*, consists of parents who did not select any of the twelve individual savings decisions or answered “No” to the survey question for whether they have made savings efforts for their student’s education after high school. The three combined savings strategies are mutually exclusive from each other and the control group. The intent of this research is to identify an influence from developing postsecondary savings in the time period before students typically begin to make college-going decisions, relative to peers who differ only in their parent’s decision to save. *Non-Intent* provides a consistent control group to examine the difference in outcomes from students who, all else equal, vary only in access to parents’ college assets. *Non-Intent* is an appropriate control group for this study because the research questions are focused on the difference in observed enrollment for students whose parents have developed college savings and the household decisions made to accumulate savings. One limitation of using *Non-Intent* as the control group is that I am not able to discuss the difference in magnitude across the treatment groups.

The *Non-Intent* student population has the same statistical probability of possessing parents’ college assets, but their parents have opted against savings. Rosenbaum and Rubin (1983) find that matching students directly on the estimate, called propensity scores (pscores), provide model outcomes that are approximately the same as comparing students individually on the study’s full vector of covariates. When a student with savings is matched with multiple students from the *Non-Intent* group, an inverse weighting process is applied. The weighting process assigns a fraction value to each *Non-Intent* paired student, such that the fractions for all students matched to a single treatment student sum to one. For instance, if two *Non-Intent* students are matched to a single student with savings, the two *Non-Intent* students are each given one-half weight; if three *Non-Intent* students are matched, each are given a one-third weight, etc.

Post-Matching Tests. Austin (2011) examines different methods for applying PSM to sociological research and concludes that PSM results have the ability to mimic randomized control experiments contingent on verifying population characteristics; for instance, a balanced, post-weight sample population with insignificant difference in pscores between matched students. I use two different methods to verify the close proximity of matches. First, Figures 21-23 demonstrate kernel density plots for pre- and post-weighting. The distance under each curve represents the full portion of the group with a particular pscore, and extends horizontally across the full range of pscores. The vertical distance between curves, the kernel density, measures the sample's proportional difference between the two groups. After applying the matched weighting there should be no discernable difference in curves horizontally or vertically, as is the case for this data.

Second, I use a statistical test to verify that the sub-populations within a sample remain equal after applying the post-match weights. Austin (2011) asserts that a regression of each covariate onto the savings treatment and a test of the coefficient estimate will identify if there is a standardized difference between the means of the treatment and *Non-Intent* population. In this regression, the intercept will take the value of the mean for the *Non-Intent* population and the coefficient (β_1) for the treatment variable will represent the difference in mean between the treatment and control group. The null hypothesis for the test is that $\beta_1 = 0$, where failing to reject the null hypothesis indicates statistically similar means. In the event that the means are not statistically different from zero, a difference of 0.10 or less is considered negligible, so that any particular population is not unduly influencing results in either the savings or control condition (Austin, 2011). Tables 34-36 chart the standardized difference and the p-value for significance that the standardized difference between the treatment and control group is equal to zero.

Unbalance can be dealt with in numerous ways, most notably to drop the affected observations or simply leave the population unbalanced. In this research, I have dropped the population with household income greater than $250,000 annually from all models because of unbalance. High-income households are much more likely to accumulate parents' college assets but this likely does not represent new savings, rather the reallocation of different savings (Dynarski, 2004; Ma, 2004). I believe that removing this population will improve matches without diminishing model results. This demographic is made up of 438 households total, with 378 of these possessing college savings. By omitting this group of households, I am not able to apply any results or implications to families with reported incomes above $250,000.

Matching Estimators. Figure 20 identifies the matching estimators used from the ELS:2002 dataset and their alignment in Perna's conceptual framework. Matching on categorical variables can be less precise than other variable types, so all matching estimators are coded as binary variables (if a student is positively identifiable by the estimator, variable=1) or continuous variables.[22] The outer layers from Perna's conceptual framework are assumed to be constant in this research because the ELS:2002 dataset contains only a single cohort of students. The macroeconomic factors present during the time of the survey are identical for all students, so a unique influence is not present. *The School and Community Context* is represented by covariates that describe the educational environment for each student: secondary school type (Catholic, private but non-Catholic, or public), a continuous variable for the percentage of students within the school that qualify for federal free/reduced lunch, and a continuous variable for the number of full-time guidance counselors.

[22] For example, the secondary school type variable "Catholic" is coded as 1= Yes, the student attends Catholic schools and 0= No, the student does not attend Catholic schools.

The student's physical environment is captured through geographic location (Northeast, South, Midwest, or West) and regional location (suburban, rural or urban). The inner layer, *Habitus*, includes covariates for gender (male), race and ethnicity (White, African-American, Hispanic, Asian/pacific islander, American Indian/Alaskan Native, or two/more identified categories), number of siblings (no siblings - 4 or more siblings). To account for student information on postsecondary enrollment I include measures for whether a parent and student discuss college and if the father and/or mother attended college. Demand for higher education is measured using variables for whether the student stated an expectation of postsecondary enrollment, whether parents stated the expectation of postsecondary enrollment, and a continuous variable for students' scores from standardized tests administered in 10th grade. Resources for postsecondary affordability are reported by household income (Income Quartiles 1 - 4).

The value of savings amassed at the time of the 2002 BY survey and changes in academic behavior after 10^{th} grade have explanatory power in predicting enrollment, but cannot be used to predict the availability of parents' college assets. PSM requires all matching estimators to be observed prior to the treatment (parents' college assets) being introduced. This helps assure that the influence of the treatment is captured by the coefficient of the treatment variable. Logically, the amount of money saved has to occur after savings is developed. Similarly, a student graduates high school after 10^{th} grade; the point in time the survey identifies whether a student has parents' college assets. To avoid potential biases from omitting these factors, I will include them in the post-match models as covariates. Amount saved is a categorical variable with eight different ordered groups, ranging from parents having savings accounts but no current value, to parents with savings in excess of $50,000. High School GPA is an ordered categorical variable starting with student GPA between 0.0 and 1.0, and increasing in 0.5 GPA increments to 3.5-4.0 GPA.

Model Specification. I use PSM to estimate the Average Treatment Effect on the Treated (ATT) for students who have parents' college assets. This provides an assessment of the average treatment outcome for members of the treatment group – postsecondary enrollment for students with parents' college assets. To arrive at estimations for the treatment condition, each model will be run as OLS and Logistic regressions. Employing both regression methods is useful in identifying the potential existence of linear and quadratic trends and is necessary when using a binary dependent variable (Agresti, 2007).

Equations 1-4 illustrate the general estimation equations. The dependent variable, *Enrollment*, is a binary variable identifying if a student enrolled in a Public or Private, two- or four-year institution. Here, I use *PCA* as a generic abbreviation for the binary combined savings treatment and only illustrate the OLS regressions, both for simplicity. As shown in Equation 1, I run unweighted, naïve regression estimates of the savings strategies to demonstrate a trend between parents' college assets and postsecondary enrollment. Equation 2 demonstrates post-matching, weighted estimates that reintroduce the pscore estimate (p_i) for student *i* into the model to capture bias between households that do and do not save (Rosenbaum & Rubin, 1983). Equation 3 includes the pscore (p_i) and individual matching estimators ($\mathbb{X}_i$) for student i, to account for any additional variation not captured by the pscore. In Equation 4, I include the pscore (p_i), individual matching estimators ($\mathbb{X}_i$), and account for student level factors that influence enrollment behavior, but that cannot be matched on: graduating high school GPA (GPA_i) and the value of parent's college assets at the time of the 2002 BY ($Amount_i$).

$$Enrollment_i = \alpha + \beta_1 PCA_i + \varepsilon_i \quad (1)$$
$$Enrollment_i = \alpha + \beta_1 PCA_i + \beta_2 p_i + \varepsilon_i \quad (2)$$
$$Enrollment_i = \alpha + \beta_1 PCA_i + \beta_2 p_i + \beta_3 \mathbb{X}_i + \varepsilon_i \quad (3)$$
$$Enrollment_i = \alpha + \beta_1 PCA_i + \beta_2 p_i + \beta_3 \mathbb{X}_i + \beta_4 GPA_i + \beta_5 Amount_i + \varepsilon_i \quad (4)$$

Next, I repeat the models demonstrated in Equations 1-4, but replace the binary combined treatment condition with the individual savings options nested within that treatment strategy, identified in Table 33. The vector for savings alternatives is represented by λ_i. Each of the individual savings options is binary, identifying if the parents' college asset portfolio for student *i* has that specific savings option. This is necessary to control for savings options that may be creating contradicting influences. I only illustrate this once for simplicity using Equation 5. Equation 5 is comparable to Equation 4, including the pscore (p_i), individual matching estimators (vector $\mathbb{X}_i$), high school graduating GPA (GPA_i), and 2002 BY amount saved ($Amount_i$).

$$Enrollment_i = \alpha + \beta_1 \lambda_i + \beta_2 p_i + \beta_3 \mathbb{X}_i + \beta_4 GPA_i + \beta_5 Amount_i + \varepsilon_i \quad (5)$$

After executing the matching models I perform a series of post-match, heterogeneous models. The heterogeneous models restrict the sample to a single group. This permits me to identify if the parents' college asset treatment is having a different influence across demographics. The post-match, heterogeneous models are run separately, restricted by race and ethnicity (White, African-American, and Hispanic), Household Income (Income Q1-Q4), student's postsecondary expectation (Unsure, expected enrollment, beyond a 4-year degree), and specific institution type of enrollment (2-year, 4-year, Public, 4-year, and Private, 4-year). These models use the same weighting as the full sample matching models described in Equations 1-5, but only include pscore (p_i), high school graduating GPA (GPA_i), and 2002 BY amount saved ($Amount_i$). It is necessary to omit the vector for individual matching estimators to increase the degrees of freedom in the model as the restricted populations have far fewer observations. Equation 6 provides an example of heterogeneous post-match models, using race and ethnicity: White.

$$Enrollment_i = \alpha + \beta_1 PCA_i + \beta_2 p_i + \beta_4 GPA_i + \beta_5 Amount_i + \varepsilon_i, \text{ if } White_i = 1 \quad (6)$$
$$Enrollment_i = \alpha + \beta_1 \lambda_i + \beta_2 p_i + \beta_4 GPA_i + \beta_5 Amount_i + \varepsilon_i, \text{ if } White_i = 1 \quad (7)$$

Methodological Limitations. In this research I must make assumptions regarding the decisions and communication of parents' college assets. I am unable to ascertain the exact point when parents began to save for their child's future education, I am only able to determine that it happened prior to the BY ELS:2002 survey. As a consequence I am unable to isolate the length of exposure to the treatment condition. I am also unable to identify whether students comprehend issues surrounding parents' postsecondary savings. While I cannot isolate direct communication on parents' college assets, I am able to identify if parents had any communication with their child regarding college.

The Conditional Independence Assumption (CIA) must be met for PSM to be valid. CIA states that no influential characteristics that predict savings are left unidentified in the model. The assumption implies that implementing covariates to explain participation in the treatment condition reduces selection bias; however, this assumption is largely untestable. Frolich (2007) has more recently questioned the degree of influence from failing to meet the CIA assumption, particularly as pscores move away from zero. Nonetheless, I have included all measurable covariates in calculating the pscore in accordance with Austin (2008).

Descriptive Statistics

Tables 37-42 provide descriptive statistics for the sample. The number of observations and the sample percentage for households that save and households in the *Non-Intent* group, broken up by student and household characteristics are first. In addition, I provide the number of observations omitted from the sample for missing information. I also provide statistics on the specific decisions made by households who have begun establishing savings. First, is the number of households that fall within the three combined savings strategies and the percentage representative of the specific demographic, and second, is the number of observations and percentage representative to the specific demographic for households that include each of the individual savings components nested in the *Past Account Creation* strategy. To complete Tables 37-41, I show the average number of savings components used by households within the specific student or household characteristic. Table 42 illustrates the correlation between pairs of savings components and the number of parents' college asset portfolios that include that pairing.

Table 37 illustrates that there are small differences in parents' college assets based on student gender. The full sample contains slightly more females than males, 52% vs. 48%, though the difference in savings is smaller than the four-percentage point difference. *Past Account Creation* (31.4% vs. 30.1%) and *Past Account Creation + Past Asset Reallocation + Future Intention* (41% vs. 39.7%) each have a higher representation for male students. Among the individual savings vehicles, only *Insurance* is less common among male students relative to female. Total, male students have a slightly higher number of savings components in their parents' college asset portfolio, 4.21 vs. 4.17.

Table 37 also shows that differences in savings strategies are more evident across racial and ethnic groups (listed in the order White, African-American, and Hispanic). White households are the most likely to develop parents' college, 56% vs. 46% vs. 35%. White households are more prone to fall within the savings strategies *Past Account Creation* (34.4% vs. 20.6% vs. 26%) and *Past Account Creation + Past Asset Reallocation* (11.3% vs. 10% vs.

8.2%). Hispanic families are more likely to use household sacrifices than African-American families, and both African-American and Hispanic families exhibit a greater likelihood to identify future household sacrifices than White families, 36.2% vs. 52.1% vs. 44.6%. *Savings* accounts are the most commonly used savings vehicle for each group, present in 73.3%, 80.9%, and 71.7%, of White, African-American, and Hispanic households, respectively. After *Savings*, *Stock/Real Estate* and college *529 plans* are the next most commonly used individual savings vehicles among White households (58.4% and 44%), while *Other Savings* and *Insurance* are the least common (28% and 32.9%). *Insurance* policies are present in 47.8% of African-American households parents' college assets, whereas *Other Savings* and *U.S. Bonds* are the least often used (30.9% and 31.8%). *Stock/Real Estate* and *Other Savings* are present in 42.4% and 35.7% of Hispanic parents' college asset portfolios. Less frequently used among Hispanic households are U.S. Bonds and college *529 plans*, 21.9% and 30.5%. On average, African-American households include the most individual components in their savings portfolio (4.42), but only 16 percentage points separate the most and least commonly used mechanisms. White households have slightly fewer savings methods in their portfolio, averaging 4.14, and Hispanic households apply the fewest with an average of 4.01.

The statistics on parents' college assets relative to income offer a few stark contrasts to the previous literature. Establishing parents' college asset increases with reported household income, as shown in Table 38. The likelihood of having parents' college assets increases by more than 12 percentage points with each higher income quartile. Combing *Past Account Creation* + *Past Asset Reallocation* + *Future Intention* is the most common strategy in all income groups. This statistic is counter to Manly and Wells' (2009) assessment that, as household income increases, families are less likely to sacrifice household resources such as those included in *Past Asset Reallocation* and *Future Intention*. A *Savings* account is the most common method of savings for all income groups; however, the average number of savings methods included in the parents' college asset portfolio increase with each income quartile. The inclusion of college *529 plans, Stock/Real Estate*, and *U.S. Bonds* increase in each higher income quartile, while *Other Savings* is the only category that decreases in frequency with higher income.

Tables 39-40 provides statistics on savings behavior by educational expectations and enrollment outcomes. Table 39 demonstrates that the percentage of students with parents' college assets increases with each high school grade point average category. The method used for savings does not appear to have any pattern. In the survey population, parents largely expect their student to attend a postsecondary institution. Approximately 59% of parents expect their student to earn up to a Bachelor's degree, whereas an additional 33% expect their student to enter graduate school. *Stock/Real Estate* is present in more than half of parents' college asset portfolios when the parents' expectation is for students to earn a 4-year degree. When parents expect a graduate degree, use of college *529 plans* increases. The number of savings mechanisms used by parents also increases with elevated degree expectations. When students are expected to attend higher education through a four-year degree, the average number of methods in the parent's college asset portfolio is 4.01, but inflates to 4.45 with higher degrees.

A student's own expectations for postsecondary enrollment align with parent's willingness to save and the number of devices they include in their savings strategy. Only one-in-three students who are unsure of their academic expectations—either they expect not to enroll, or have not established a college going plan by 10th grade—have parents that save. In comparison, nearly 50% of students expecting to attend a 4-year institution as their highest educational attainment have parents' college assets. Students with graduate school expectations have the greatest likelihood of parents that save. Regardless of student expectations, *Stock/Real Estate* is present in over 50% of parents' college assets. Again, college *529 plans* increase in use with the expectation of graduate school.

In my sample, 77% (8,547 out of 11,039) of surveyed students enrolled in postsecondary institution immediately following high school. The largest number of these students (5,404) enrolled at a 4-year institution. The trend for enrollment reflects possession of parents' college assets. Among students who have any form of savings, enrollment rates are higher at 4-year institution types. In particular, 58.9% of families who established *Stock/Real Estate* in their portfolio saw their student enroll in a 4-year institution. College *529 plans* are associated with the lowest enrollment at 2-year institutions and the lowest rate of non-enrollment. The control, *Non-Intent* group represented the largest percentage of students who did not enroll or who enrolled in a 2-year institution.

The correlation between different savings mechanisms used in a savings portfolio and the number of families that employ each combination is reported in Table 42. The correlation matrix demonstrates that families use savings options on the opposite end of the perceived risk spectrum: higher-risk alternatives are paired with low-return, safer methods. This is most evident with investing in *Stock/Real Estate* with traditional *Savings* accounts and *U.S. Bonds*. The number of families that use this specific combination outnumber families at the top of the income distribution. This is evidence that low and middle-income families are among the population that uses high risk/high reward strategies to finance education. Parents' college asset portfolios that include *529 plans* have low correlations with other methods. Given the alignment with tuition, families likely feel more secure that these are the best chance for a return that will cover educational costs. This indicates that parents are less willing to spread savings to other vehicles.

Results

PSM is used to reduce the bias in the prediction estimates for the decision to enroll in higher education based on the postsecondary savings decisions made by parents. All models are run using both OLS and Logistic regression. A binary dependent variable, such as *Enrollment*, allows the OLS parameter estimates to be interpreted as percentages by multiplying the coefficient of interest by 100 (β_1x100). The Logistic models provide estimates of the Odds Ratio (OR). ORs are non-linear estimators based on the probability of having parents' college assets: a one-unit increase in the pscore elevates the odds of enrolling, above a student in the *Non-Intent* control group, by the value of the coefficient. All OR coefficients are positive. A coefficient greater than one is a signal that a student with parents' college assets has greater odds of enrolling. A coefficient value between zero and one identifies a negative influence − a student with parents' college assets having lower odds of enrolling. Percentages are typically more intuitive to interpret, so I will use these results in the following explanations. I will discuss the results of the Logistic models only when they conflict with the OLS estimator.

I present the results for the models in two different ways. First, I present the results using the binary combined strategy as the treatment condition. After, I substitute the combined strategy treatment variable for the individual methods that align with the strategy. The first set of outcomes identify if the cumulative savings portfolio can statistically predict a student's decision to enroll. The second set of outcomes identify if any of the individual savings decisions used by parents are statistically associated with a student's enrollment decision; and whether any individual components of a savings portfolio have a negative coefficient which would reduce the net estimated association. If the coefficients for various savings methods have opposite signs, the combined strategies are biased toward zero.

The model results are presented in Tables 43a-57b. The table numbering is ordered by combined treatment strategy: *Past Account Creation* (Tables 43a-47b), *Past Account Creation + Past Asset Reallocation* (Tables 48a-52b), and *Past Account Creation + Past Asset Reallocation + Future Intention* (Tables 53a-57b). Tables lettered "a" present the model results using the combined treatment variables. Tables lettered "b" provides the results for models that use the individual savings methods treatment variables in place of the combined strategy. For example, the *Past Account Creation* treatment variable is replaced with the six savings methods *Savings*, *Insurance*, *U.S. Bonds*, *Stock/Real Estate*, *Other Savings*, and *529 plan*. The tables for both letters are organized in the same manner.

Tables 43a-b, 48a-b, and 53a-b present the results for each treatment condition including naïve, unweighted models (Models 1-2), the PSM matched estimator (Model 3), and post-match, weighted models (Models 4-9). The post-match models are conditioned on pscore (Models 4-5), pscore and the matched covariates (Models 6-7), and pscore, matched covariates, amount saved by 10th grade, and high school graduating GPA (Models 8-9). PSM does not provide estimates for the individual variables used in the matching process, so Model 3 is omitted in Tables lettered "b". The sample size and r-squared/pseudo r-squared values are reported for all tables.

There are a number of demographic combinations can provide valuable insight into savings behaviors and outcomes. For example, prior research has described differences in household saving behavior based on student's gender and race and ethnicity (Beverly & Sherraden, 1999; Elliott, 2011; Elliot & Beverly, 2010; Hillman, Gast & George-Jackson, 2015; Hossler & Vesper, 1993; Okech, Little & Shanks, 2011; Stage & Hossler, 1989). I will examine models by gender and race and ethnicity. Ideally, I would like to assess models for more specified student populations. Splitting the sample population further results in small sample sizes so I am unable to examine multiple student demographics simultaneously (for instance, gender by race and ethnicity). For this reason I opt to only include models for single demographic characteristics for this assessment.

Tables 44a-b, 49a-b, and 54a-b present treatment results restricting the sample population based on student's gender and race and ethnicity: Male (Models 1-2), Female (Models 3-4), White (Models 5-6), African-American (Models 7-8), and Hispanic (Models 9-10). Tables 45a-b, 50a-b, and 55a-b present the results based on reported household income: $0-25,000 (Models 1-2), $25,001-50,000 (Models 3-4), $50,001-75,000 (Models 5-6), and $75,001-100,000 (Models 7-8). Tables 46a-b, 51a-b, and 56a-b present the results based on student's postsecondary expectations in 10th grade: Unsure (Models 1-2), Postsecondary Expectations for enrollment (Models 3-4), Postsecondary Expectations to earn a college degree beyond a Bachelor's degree (Models 5-6). Finally, Table 47a-b, 526a-b, and 57a-b presents the results of the specific institutional enrollment type: 2-yr (Models 1-2), 4-yr (Models 3-4), Public, 4-yr (Models 5-6), and Private, 4-yr (Models 7-8). The tables for the heterogeneous model results are conditioned on pscore, amount saved by 10th grade, and high school graduating GPA. This is necessary to avoid overly specifying the models.

Past Account Creation. Tables 43a-b includes families with a savings strategy that qualifies as *Past Account Creation*, those that possess individual financial accounts to hold savings but have not identified any specific methods to accrue resources. The naïve results demonstrate that households with the combined *Past Account Creation* strategy (Table 43a) are significantly associated with positive enrollment behaviors 20.2 percentage points (p<0.001) above students from the *Non-Intent*, control group (Models 1-2). For the matched result (Model 3), *Past Account Creation* is statistically linked to increase the chances of enrollment by 4.3 percentage points ($p<0.001$). This finding is consistent across the post-match Models 4-7. The parameter estimates become insignificant in Models 8-9 after adding post-treatment variables for amount saved by 10th grade and graduating high school GPA. Table 43b demonstrates that the naïve estimators (Models 1-2) for the combined strategy are being driven by households that use *Savings*, *U.S. Bonds, Stocks/Real Estate*, and college *529 plans*. I find in the weighted, post-treatment models that opening a college *529 plan* provides a non-linear, significant enrollment increase in Model 7 (1.61 OR)($p<0.05$) and Model 9 (1.71 OR)($p<0.05$). Additionally, Models 8-9 illustrate that *Other Savings* is providing a significant, negative coefficient on enrollment of 4.3 percentage points ($p<0.05$).

I find the combined *Past Account Creation* strategy has no significant influence on enrollment when restricting the models by student's gender or race and ethnicity in Table 44a. Table 44b shows that using a college *529 plan* is significantly associated with a 5.3 percentage point ($p<0.001$) (Models 5-6) increase in enrollment for White students.

In Tables 45a-b, I restrict the models by income quartile and find *Past Account Creation* significantly increases the likelihood of enrollment by 15.8 percentage points ($p<0.001$) (Table 45a, Models 5-6) for families who make between $50,001 and $75,000 annually. After substituting the combined strategy for the individual options in Table 45b I find college *529 plans* and *Other Savings* have contradicting magnitudes. College *529 plans* has significant, positive non-linear results (2.84 OR)($p<0.05$) for households in Income Q3 (Model 6) and predicts enrollment increases of 8.1 percentage points ($p<0.05$) for households in Income Q4 (Models 7-8). Among Income Q2 households (Models 3-4), *Other Savings* statistically predicts a decreased likelihood of student enrollment by 15.9 percentage points. Families within Income Q3 are statistically 11.3 percentage points ($p<0.05$) less likely to have a child enroll when they include *Other Savings* in their strategy.

Tables 46a-b present results based on student's postsecondary expectations. I find no significant results that the combined *Past Account Creation* strategy (Table 46a) increases observed enrollment. Table 46b shows that college *529 plans* predicts a positive 3.1 percentage point ($p<0.05$)(Models 5-6) for enrollment among students with expectations to earn beyond a four-year degree.

Lastly, Tables 47a-b details the results for institutional enrollment type. In Table 47a I find that *Past Account Creation* is not significantly associated with enrollment at a specific postsecondary institutional type. Shown in Table 47b, college *529 plans* are statistically linked with increased observed enrollment by 5 percentage points ($p<0.05$) at any four-year institution type (Models 3-4) and a 1.36 ($p<0.05$) non-linear increase at Private, four-year institutions (Model 8).

Past Account Creation + Past Asset Reallocation. The combined strategy, *Past Account Creation + Past Asset Reallocation*, represents households with a savings strategy including individual savings vehicles and specific household decisions for redirecting resources for postsecondary savings. The naïve models in Table 48a show that households with *Past Account Creation + Past Asset Reallocation* significantly more likely to enroll by 18.1 percentage points ($p<0.001$), relative to students from the *Non-Intent*, control group (Models 1-2). The matched results (Model 3) and post-match results (Models 4-7) are insignificant for this combined strategy. Interestingly, after conditioning on the amount saved and graduating GPA, *Past Account Creation + Past Asset Reallocation* increases the likelihood of a student's postsecondary enrollment by 9.6 percentage points ($p<0.001$)(Models 8-9). The naïve, unweighted estimators for the individual savings decisions show *U.S. Bonds*, *Stock/Real Estate*, college *529 plans*, *Add Job*, *Reduce Expenses*, and *Remortgage* are significantly, positively associated with postsecondary enrollment in Table 48b. However, no individual savings decisions are significant in Models 8-9.

Restricting the population for the heterogeneous models creates sample size problems in the remaining tables for this combined strategy. Moving forward, I will only report results when the binary combined strategy model has at least 10 observations for the variable in the model. In Table 49a I find no evidence that parents' college assets is associated with enrollment based on student's gender, but I do find correlations based on race/ethnicity. White students with the combined *Past Account Creation + Past Asset Reallocation* strategy are observed enrolling at a increased rate, 9.7 percentage points ($p<0.05$)(Models 5-6), relative to students from the *Non-Intent* group. By comparison, Hispanic students are less likely to enroll when their parents use a *Past Account Creation + Past Asset Reallocation* combined strategy. The enrollment prediction for the combined strategy is statistically significant and non-linear (Model 10). Model 9 approximates a 24-percentage point ($p<0.1$) decreased likelihood of enrollment.[23] I find a negative connection between using *Insurance* (0.293 OR)($p< 0.05$) and *Other Savings* (0.331 OR)($p< 0.05$) for Male student enrollment. Using Remortgage to develop parents' college assets for Female students is linked to a 13.3 ($p<0.001$) percentage point increase in enrollment. I find a 6.5 percentage points (3.0 OR)($p<0.05$) increase in enrollment among White students (Table 49b, Model 5-6) when parents include *U.S. Bonds*. African-American students are statistically, positively more likely to enroll when parents use *Savings* and college *529 plans* in their savings

[23] Model 5 is only significant at the 90% confidence interval. It is reported here only to provide magnitude to the non-linear influence found in Model 6.

portfolio (Models 7-8). Hispanic students are less likely to enroll by 58 percentage points ($p<0.05$)(Model 9) when parents alter their work schedule, *Add Job*, to develop postsecondary savings. This correlation is offset when parents open a college *529 plan* (73 percentage points)($p<0.05$).

When I restrict the models based on household income, Table 50a shows that students from households earning between $75,000 and $100,000 are 12.5 percentage points ($p<0.05$) more likely to enroll when using the *Past Account Creation + Past Asset Reallocation* combined strategy. Table 50b shows that students from the lowest income quartile, Income Q1, have a negative, non-linear response to enrollment when parents *Reduce Expense* (Model 2) to incur savings. Students who reside in households earning between $25,001 and $50,000 (Models 3-4) have multiple significant predictors. *U.S. Bonds* (17.4 percentage points)($p<0.05$) and *Remortgage* (24.7 percentage points)($p<0.05$) have positive magnitudes for enrollment, but *Other Savings* presents a negative 18.9 percentage points ($p<0.1$) likelihood for students. Students from Income Q4 (Models 7-8) households are more likely to enroll when parents *Add Job* (12 percentage points)($p<0.05$) and *Reduce Expense* (10.5 percentage points)($p<0.05$), but the likelihood is offset when parents use *Stock/Real Estate*, 19 percentage points ($p<0.05$), to build savings.

Tables 51a-b have significant findings based on student's postsecondary expectations. Table 51a shows that the combined *Past Account Creation + Past Asset Reallocation* strategy increases the likelihood of enrollment for students who expect to enroll in college (8.6 percentage points)($p<0.05$) and students who intend to earn beyond a four-year degree (8.3 percentage points)($p<0.05$). In Table 51b I find that *Add Job* (36.7 percentage points)($p<0.05$) increases the likelihood of enrollment for students who were unsure of their postsecondary expectations. Models 5-6 show that opening a college 529 plan increases enrollment 5.1 percentage points ($p<0.05$) for students who expect to earn beyond a four-year degree.

Table 52a shows that the combined strategy does not promote enrollment at any specific postsecondary institution type. The insignificant results in Table 52a are the result of conflicting significant predictors from the individual savings decisions, illustrated in Table 52b. Households that include *Other Savings* in their portfolio improve the chance of enrollment to two-year institutions by 10.6 percentage points ($p<0.05$)(Models 1-2), however *Remortgage* decreases the likelihood by 12.6 percentage points ($p<0.05$). The opposite of these findings are true for observed enrollment at four-year institutions. *Other Savings* decrease the chance of enrollment at four-year institutions by 12.1 percentage points ($p<0.001$)(Models 3-4) while *Remortgage* increases the probability of enrollment by 12.7 percentage points ($p<0.05$). College *529 plans* decrease the likelihood of enrollment by 8.4 percentage points ($p<0.05$) at Private, four-year institutions (Models 7-8). For the same institution type, *Reduce Expenses* increases the chance of enrollment by 10.0 percentage points ($p<0.05$)(Models 7-8).

Past Account Creation + Past Asset Reallocation + Future Intention. The combined strategy *Past Account Creation* + *Past Asset Reallocation* + *Future Intention* identifies households who have established savings vehicles to hold savings, redirected household assets to build savings, and state the intent to add to redirect future household assets to build savings beyond 10th grade. Table 53a illustrates that the naïve models (Models 1-2) for the combined strategy are significantly associated with an 18.8 percentage point ($p<0.001$) increase in enrollment (Models 1-2). For the matched results (Model 3) I find a 4.9 percentage point ($p<0.001$) estimate from this combined strategy. The significance and magnitude for the match result carry through the post-match Models 4-7. The models lose statistical significance when adding post-treatment variables in Models 8-9.

I find that *U.S. Bonds*, *Stock/Real Estate*, college *529 plans*, and *Plan to Reduce Expenses* are all significant and positively associated with enrollment in the naïve models (Models 1-2) in Table 53b. A savings portfolio that includes *Other Savings* carries a positive coefficient in Models 8-9 and increases the chances of enrollment by 4.2 percentage points ($p<0.001$).

In Table 54a, I find that no significant results for the combined strategy when restricting the models on student's gender or race and ethnicity. There are a number of individual savings options that align with improved enrollment for Female students. Most notably, *U.S. Bonds* ($p< 0.05$) and *Planned Remortgage* ($p< 0.05$) increase the percentage by approximately 5 percentage points, each. *Add Job* ($p< 0.05$) decreases the observed enrollment by 4.1 percentage points. College *529 plans* provide a positive 3.6 percentage point ($p<0.05$) prediction of enrollment among White students (Model 3), as shown in Table 54b.

Table 55a demonstrates that households in Income Q2 (Models 3-4) increase the chance of their student enrolling by 9.4 percentage points ($p<0.05$) when using *Past Account Creation + Past Asset Reallocation + Future Intention.* Households falling within Income Q4 (Models 7-8) increase the probability of enrollment by 5.1 percentage points ($p<0.001$) with the combined strategy. In Table 55a using *U.S. Bonds* increases enrollment by 5.2 percentage points ($p<0.05$) for households reporting income between $50,001 and $75,000 (Models 5-6). *Stock/Real Estate* decreases the likelihood of a student enrolling from the highest income quartile (Models 7-8).

In Table 56a, Models 3-6 show that the combined *Past Account Creation + Past Asset Reallocation + Future Intention* strategy has a positive correlation for enrollment by students who expect to enroll in college (5.1 percentage points)($p<0.05$) and students who expect to earn beyond a four-year degree (4.8 percentage points)($p<0.05$). Among students who expect to enroll, *Other Savings* produces a positive 3.7 percentage point ($p<0.05$) increase in enrollment (Table 49b, Models 3-4).

Table 57a shows the combined strategy is not significant in increasing enrollment at any specific institution type. Table 57b illustrates conflicting predictors on postsecondary institution type based on the savings decisions. In Models 3-4, students with Savings are 5.3 percentage points ($p<0.05$) less likely to enroll at four-year institutions. However, students with college *529 plans* are 5.7 percentage points ($p<0.001$) more likely to enroll at the same institution type. *Reduce Expenses* is associated with students increasing enrollment at Public, four-year institutions by 6.9 percentage points ($p<0.05$)(Models 5-6), but using *Remortgage* to increase savings creates a contradictory relationship of 6.8 percentage points ($p<0.05$). *Savings* reduces the chances of enrollment at Private, four-year institutions by 5.6 percentage points ($p<0.05$) (Models 7-8).

Discussion

The stated intent of the research is to add further insight to the field of parents' college assets and postsecondary enrollment. Previous research has either amassed all savings into a singular influence, or isolated individual methods (Elliott, 2011; Elliott & Beverly, 2010; Elliott, Song, & Nam, 2013; Hossler & Vesper, 1993). My contribution is an examination of how strategic grouping of individual savings methods are associated with unique, dissimilar outcomes on the likelihood of enrollment. This extends beyond treating all parents' college assets equally and assumes that there is no single "silver bullet" for postsecondary savings.

The descriptive statistics illustrate that parents are not confident in the ability of any single savings device to create postsecondary affordability. Parents appear to use a strategy that diversifies their savings portfolio by including risk and risk-free methods. This is true even when using savings devices that are created specifically for postsecondary education. This finding coincides with previous literature and statistics on postsecondary savings habits (Ma, 2004; Manly & Wells, 2009; Sallie Mae, 2013). The returns from the six *Past Account Creation* options provide vastly different levels of return and have different incentives for use. Financially, spreading capital across multiple savings mechanisms may not be achieving the same financial gains and may not be increasing the chances of postsecondary access.

The spread of parents' asset accumulation strategies increases the risk of including strategies with contradictory associations with enrollment. The results of this study demonstrate that, on average, the cumulative decisions by parents to establish college assets are sensitive to environmental factors and the combination of other savings devices. After conditioning on factors such as expectations, income, academic aptitude, and amount saved, the process of developing savings does not provide a stimulant to postsecondary enrollment. This is contradictory to previous literature that describes the act of saving as producing mental accounting and financial management capabilities. Matched models with positive enrollment predictors from savings lose explanatory power when incorporating post-matching factors. This finding is important, but it does not fully address whether parents are "in the driver's seat" with regard to creating postsecondary enrollment. When examining the association with individual savings methods, however, a different story emerges.

The findings I present in this research support the hypothesis that parents' savings decisions improve the likelihood of their child enrolling in a postsecondary institution. The models that match on individual savings methods identify that parents may be inadvertently diminishing the anticipated outcomes of savings by being overly ambitious. The combination of strategies impacts the perceptions and environment the student resides in. Despite signaling affordability, students also receive the perception of a high level of household sacrifice. Perna (2006) described that the context of postsecondary information can overshadow the aspirations and resources available for enrollment. I believe that this research provides additional support for this idea, and adds the process of parent savings to applicability. This is most notable for households that use unconventional savings methods, identified as *Other Savings* in this research. The inclusion of *Other Savings* in a savings portfolio provides a statistically significant, negative likelihood of? enrollment overall (see Table 43b.) and for several student demographics.

As I hypothesized, the impact from parents' college assets is not uniform across student populations. When limiting the sample to underrepresented populations, very few savings methods are associated with bolstering enrollment. The models for savings strategies that include household sacrifices validate the significant, negative results I hypothesized. This is most noticeable when additional employment is used to accrue assets. We can interpret these findings in different ways. One, students may observe the additional work hours and opt to forego college so those assets can be redirected elsewhere. This assumes that students understand the additional work is for their enrollment funding, but this cannot be validated in this data though. A comparable interpretation is that the additional labor hours alter the student's environment in ways that are not conducive to enrollment.

One limitation of the research presented here is the inability to discern what information students have on postsecondary savings. Stated differently, how much do parents tell students? This should be a direction for future researchers; however, it does not undermine the interpretation of my findings. First, the literature review identifies the multiple ways that parents are involved in the college going decision-making process. This makes it difficult to believe that a component of this involvement does not include some information on affordability and savings. Secondly, and most related to this study, the substantial findings of this research involve the characteristics that are visible to students. Reducing expenses and adopting a new work schedule each alter a student's direct environment. Even when a student is not informed of the specific reason, incentives are still transformed in the same direction. Each of these trade-offs directly involves the household's monetary resources. If a student believes the sacrifices are being made on their account, the explanations described above would apply. In an alternate circumstance, if a student is not aware of why the sacrifices are being made, they are still conscious of the household's financial standing. When engaged in the college-going decision-making process, this is likely to be included in the assessment of affordability. As identified by Perna (2004), the weight applied to social and cultural context can supersede direct information. If a student is given positive feedback on affordability, the actions they observe in their environment offset the perception.

Policy Implications

As public policy continues to move away from socially financing higher education, the role of parents' college assets will continue to grow, as will policy debate on the incentives used to promote savings. An assessment of the gains to student enrollment based on parents' college assets holds great significance for this reason. Most external mechanisms awarding financial aid are unavailable until the final stages of the enrollment process, well after the decision to attend has been made. Savings represents one of the few available alternatives for families to minimize the future out of pocket costs of attendance. As such, household savings represents a form of early information on postsecondary affordability.

The descriptive statistics show that parents use a “mix and match” practice for establishing their savings portfolio. There is no prevailing rationale for the pairing of savings methods used by parents, with the potential exception of the level of risk that would be incurred. Families with limited financial awareness or access to financial institutions may be unaware of the nuances of tax policy and the full range of potential benefits (Olivas, 2003). This could unintentionally reduce their desire to invest or promote the idea of including a range of other savings methods. Policy expansion used to promote self-financing of higher education must consider the role of savings institutions to this extent.

Olivas (2003) described that state subsidies may negatively impact the number of state and federal college investment funds. The author contends that subsidies can be reduced based on the availability of personal financing programs such as 529 college savings plans and Coverdell educational accounts. As a larger number of savings and finance options become available, so too does the capability of individual families to cover a greater fraction of the cost of education. My findings suggest that the assumptions regarding savings do not hold for all student populations, and can disproportionately hurt students on the margin of access.

Policy that would incorporate pre-established savings plans for students (or children) have been debated numerous times over the last several years, as well as tax policy aligned with educational savings (Carrns, 2015; Elliott, 2009; Elliott & Beverly, 2011). My findings suggest that the creation of a savings plan may not be sufficient to induce a college-aspiring culture among underrepresented populations. Households need information on efficient ways to develop capital to save. This includes additional knowledge on the unintended consequences I have identified in this research. A more in-depth understanding on student responsiveness is necessary.

For all of the above reasons, further research is needed on the effects of parents' college assets. The research findings here illuminate that parents' savings can help promote postsecondary attendance for some students in some circumstances. A more complete understanding on the circumstances and strategies used by parents may help generate greater usage of savings, but this research does not currently exist. Additional research on the influence of parents' college assets should not be relegated to enrollment outcomes, though. For instance, student loans may be viewed as a safety net for families who are not able to save, and may be the reason we witness a difference in savings and postsecondary expectations. This may alter their strategy and indirectly change how a student perceives the importance of higher education. Recent issues with student loan availability have illustrated that excessive debt, particularly when unemployment issues are present, may be hindering individual standards of living and potential economic growth (Burdman, 2005). A future direction for this research is to tackle the question of how parents' college assets correlate with student debt.

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Appendix A – Tables

Table 1.

Sample Population Characteristics for Residency-Based Financial Aid Programs, separated by State and Cluster Analysis Results.

		Program Characteristics												Cluster Identity		
Program Name	State	City?	Early?	Committed?	Last Dollar?	Percentage?	Flat?	GPA?	ACT?	Income?	Select?	2-yr?	4-yr?	Ward	Avg.	Wgt. Avg.
Alaska Performance Grant	AK	No	No	No	No	No	Yes	Yes	Yes	No	No	Yes	Yes	1	1	1
Alabama Student Assistance Program	AL	No	No	No	No	No	Yes	No	No	Yes	Yes	Yes	Yes	1	1	1
Arkadelphia Promise	AR	Yes	No	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	3	1	3
Arkansas Academic Challenge Scholarship	AR	No	No	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	1	1	1
El Dorado Promise	AR	Yes	Yes	Yes	No	Yes	No	No	No	No	No	Yes	Yes	3	3	3
Great River Promise Scholarship	AR	Yes	No	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	3	3	3
Great River Promise - Phillips	AR	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
School Counts!: Morrilton	AR	Yes	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	Yes	3	3	3
ASU Barack Obama Scholarship	AZ	No	No	Yes	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
Promise of the Future	AZ	Yes	Yes	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	3	3	3
Blue and Gold Opportunity Plan	CA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Cal Grant A / Cal Grant B	CA	No	No	No	No	No	Yes	Yes	No	Yes	No	Yes	Yes	1	1	1
Claremont McKenna College	CA	No	No	No	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
Connecticut College	CA	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
The Cuesta Promise	CA	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	3	3	3
The Fulfillment Fund	CA	Yes	No	No	No	No	Yes	Yes	No	No	No	Yes	Yes	3	3	3
Long Beach College Promise	CA	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	3	3	3
Oakland Promise	CA	Yes	Yes	Yes	No	No	Yes	Yes	No	Yes	No	Yes	Yes	3	3	3
* PACE Promise	CA	Yes	No	Yes	No	No	Yes	Yes	No	No	Yes	No	Yes	3	2	2
Pomona College	CA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
San Francisco Promise	CA	Yes	No	No	Yes	No	No	Yes	No	No	Yes	Yes	Yes	2	2	2
SBCC Promise	CA	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
Siskiyous Promise	CA	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
Stanford University	CA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Ventura College Promise	CA	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	3	3	3
West Hills President's Scholars	CA	No	No	Yes	Yes	No	No	Yes	No	No	No	Yes	No	1	1	1
West Valley College Community Grant	CA	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
Youth 2 Leaders Education Foundation	CA	Yes	No	No	Yes	No	No	No	No	No	No	Yes	Yes	3	3	3
Commitment to Colorado	CO	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Denver Scholarship Foundation	CO	Yes	No	Yes	No	No	Yes	Yes	No	Yes	No	Yes	Yes	3	3	3
Bridgeport Tuition Plan	CT	Yes	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
New Haven Promise	CT	Yes	Yes	Yes	No	Yes	No	Yes	No	No	No	Yes	Yes	3	3	3
Wesleyan University	CT	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
DCTAG	DC	Yes	No	No	No	No	Yes	No	No	Yes	Yes	Yes	Yes	3	3	3
Delaware SEED Scholarship	DE	No	No	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	No	1	1	1
* Inspire Scholarship	DE	No	No	No	No	No	Yes	Yes	No	Yes	Yes	No	Yes	1	1	2
American Dream Scholarship	FL	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	No	3	3	3
Bright Futures Scholarship Program	FL	No	Yes	Yes	Yes	No	No	No	Yes	No	No	Yes	Yes	1	1	1
Buffalo Scholarship Foundation	FL	Yes	No	No	No	No	Yes	No	No	No	Yes	Yes	Yes	3	3	3
Machen Florida Opportunity	FL	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2

Note. *City* signifies if the geographic region for eligibility is within a county or smaller. *Early* shows if students earn eligibility prior to entering high school. *Committed* signals if aid award is distributed to all eligible students. *Last Dollar*, *Percentage*, and *Flat* identify the aid distribution method. *GPA*, *ACT*, and *Income* identify if sub-qualifications are used for eligibility. *Select* determines if award is only redeemable at a select subset of institutions. *2-yr* and *4-yr* describe the institution type aid can be redeemed. Cluster Identity labels: 1=State-Based, 2=Institutional, and 3= Community-Sustained.

* denotes programs that are not placed in consistent groups across clustering methods.

Table 1. *cont*.

Sample Population Characteristics for Residency-Based Financial Aid Programs, separated by State and Cluster Analysis Results.

		Program Characteristics												Cluster Identity		
Program Name	State	City?	Early?	Committed?	Last Dollar?	Percentage?	Flat?	GPA?	ACT?	Income?	Select?	2-yr?	4-yr?	Ward	Avg.	Wgt. Avg.
Pensacola Pledge Scholars	FL	Yes	No	No	No	No	Yes	No	No	No	Yes	No	Yes	2	2	2
Rosen Foundation Scholarship	FL	Yes	No	Yes	Yes	No	No	No	No	No	No	Yes	Yes	3	3	3
Emory Advantage	GA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Georgia Tech Promise	GA	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
HOPE Scholarship / Zell Miller Grant	GA	No	Yes	Yes	No	Yes	No	Yes	No	No	No	Yes	Yes	1	1	1
Grinnell College	IA	No	No	No	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
Chicago Star Scholarship	IL	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	No	3	3	3
Dell and Evelyn Carroll Scholarship	IL	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
Galesburg Promise	IL	Yes	Yes	Yes	No	Yes	No	No	No	No	Yes	Yes	No	3	3	3
Harper College Promise	IL	Yes	No	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	3	3	3
Huskie Advantage Program	IL	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Illinois Promise	IL	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Northwestern University	IL	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Odyssey Scholarship	IL	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Peoria Promise	IL	Yes	Yes	Yes	No	Yes	No	No	No	No	Yes	Yes	Yes	3	3	3
Rockford Promise	IL	Yes	No	No	No	No	Yes	No	No	No	No	Yes	Yes	3	3	3
UChicago Promise	IL	Yes	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
College Bound Scholarship	IN	Yes	Yes	Yes	No	Yes	No	Yes	No	No	No	Yes	Yes	3	3	3
Purdue Promise	IN	No	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	No	Yes	2	2	2
Twnety-First Century Scholars	IN	No	Yes	Yes	Yes	No	No	Yes	No	Yes	No	Yes	Yes	1	1	1
* ISU 4U Promise	IO	Yes	Yes	Yes	No	Yes	No	No	Yes	No	Yes	No	Yes	3	2	4
Cardinal Covenant	KY	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	2	2	2
Community Scholarship Program	KY	Yes	No	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	3	3	3
Hopkinsville Rotary Scholars	KY	Yes	Yes	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	3	3	3
KEES	KY	No	No	Yes	No	No	Yes	Yes	No	No	No	Yes	Yes	1	1	1
Kentucky College Access Program Grant	KY	No	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
School Counts!:Madisonville	KY	Yes	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	3	3	3
Louisiana GO Grant	LA	No	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
TOPS	LA	No	No	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	1	1	1
Amherst College	MA	No	No	Yes	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
B.U. Community Service Award	MA	Yes	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
College of Holy Cross	MA	Yes	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Harvard University	MA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Massachusetts MASSGrant	MA	No	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
MIT	MA	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Tufts University	MA	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Williams College	MA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Garrett County Scholarship Program	MD	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
Maryland Pathways	MD	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Bowdoin College	ME	No	No	Yes	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2

Note. *City* signifies if the geographic region for eligibility is within a county or smaller. *Early* shows if students earn eligibility prior to entering high school. *Committed* signals if aid award is distributed to all eligible students. *Last Dollar*, *Percentage*, and *Flat* identify the aid distribution method. *GPA*, *ACT*, and *Income* identify if sub-qualifications are used for eligibility. *Select* determines if award is only redeemable at a select subset of institutions. *2-yr* and *4-yr* describe the institution type aid can be redeemed. The ISU4U program is omitted from discussion in the typology because it was isolated in all cluster results. Cluster Identity labels: 1=State-Based, 2=Institutional, and 3= Community-Sustained.

* denotes programs that are not placed in consistent groups across clustering methods.

Table 1. *cont*.

Sample Population Characteristics for Residency-Based Financial Aid Programs, separated by State and Cluster Analysis Results.

		Program Characteristics												Cluster Identity		
Program Name	State	City?	Early?	Committed?	Last Dollar?	Percentage?	Flat?	GPA?	ACT?	Income?	Select?	2-yr?	4-yr?	Ward	Avg.	Wgt. Avg.
Colby College	ME	No	No	No	Yes	No	No	No	No	No	Yes	Yes	Yes	2	2	2
State of Maine Grant	ME	No	No	Yes	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
Baldwin Promise	MI	Yes	No	Yes	Yes	No	No	No	No	No	No	Yes	Yes	3	3	3
Bay Commitment Scholarship	MI	Yes	Yes	No	No	No	Yes	No	No	No	Yes	Yes	Yes	3	3	3
Benton Harbor Promise	MI	Yes	Yes	Yes	No	Yes	No	No	No	No	No	Yes	No	3	3	3
Campus and Community	MI	Yes	No	No	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
Detroit College Promise	MI	Yes	No	Yes	No	No	Yes	No	No	No	No	Yes	Yes	3	3	3
Detroit Scholarship Fund	MI	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
Hazel Park Promise	MI	Yes	No	Yes	No	Yes	No	No	No	No	No	Yes	Yes	3	3	3
Jackson Legacy	MI	Yes	Yes	No	No	No	Yes	Yes	No	No	Yes	Yes	Yes	3	3	3
Kalamazoo Promise	MI	Yes	Yes	Yes	No	Yes	No	No	No	No	No	Yes	Yes	3	3	3
Lansing Promise	MI	Yes	No	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	3	3	3
Legacy Scholars	MI	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
Michigan M-PACT	MI	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Michigan Tuition Grant	MI	No	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
Michigan Tuition Incentive Program	MI	No	Yes	Yes	Yes	No	No	No	No	Yes	No	Yes	Yes	1	1	1
Muskegon Promise	MI	Yes	Yes	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	3	3	3
Northport Promise	MI	Yes	No	Yes	No	Yes	No	No	No	No	No	Yes	Yes	3	3	3
Pontiac Promise	MI	Yes	Yes	Yes	No	Yes	No	No	No	No	No	Yes	Yes	3	3	3
Saginaw Promise	MI	Yes	No	Yes	No	Yes	No	No	No	No	No	Yes	Yes	3	3	3
Spartan Advantage	MI	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Carleton College	MN	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Minnesota State Grant	MN	No	No	Yes	Yes	No	No	No	No	Yes	No	Yes	Yes	1	1	1
Power of YOU	MN	Yes	No	No	Yes	No	No	No	No	Yes	Yes	Yes	Yes	3	3	3
Access Missouri Financial Assistance	MO	No	No	Yes	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
Missouri A+ Scholarship Program	MO	Yes	No	Yes	Yes	No	No	Yes	No	No	No	Yes	No	3	3	3
Washington University St. Louis	MO	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Mississippi Tuition Assistance Grant	MS	No	No	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	1	1	1
Appalachian ACCESS	NC	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Carolina Covenant	NC	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Cleveland County Promise	NC	Yes	Yes	Yes	No	Yes	No	No	No	No	No	Yes	Yes	3	3	3
Davidson College	NC	No	No	Yes	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
Duke University	NC	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Pack Promise	NC	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
VanGuarantee	NC	Yes	No	Yes	Yes	No	No	Yes	No	Yes	No	Yes	No	3	3	3
North Dakota Academic Scholarship	ND	No	No	No	No	No	Yes	Yes	No	No	Yes	Yes	Yes	1	1	2
North Dakota Student Incentive Grant	ND	No	No	Yes	No	No	Yes	No	No	No	No	Yes	Yes	1	1	1
Collegebound Nebraska	NE	No	No	No	Yes	No	No	Yes	No	Yes	Yes	No	Yes	2	2	2
Dartmouth College	NH	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Cooperman College Scholarship	NJ	Yes	No	No	Yes	No	No	Yes	No	Yes	Yes	No	Yes	3	3	3

Note. *City* signifies if the geographic region for eligibility is within a county or smaller. *Early* shows if students earn eligibility prior to entering high school. *Committed* signals if aid award is distributed to all eligible students. *Last Dollar*, *Percentage*, and *Flat* identify the aid distribution method. *GPA*, *ACT*, and *Income* identify if sub-qualifications are used for eligibility. *Select* determines if award is only redeemable at a select subset of institutions. *2-yr* and *4-yr* describe the institution type aid can be redeemed. Cluster Identity labels: 1=State-Based, 2=Institutional, and 3= Community-Sustained.

* denotes programs that are not placed in consistent groups across clustering methods.

Table 1. *cont*.

Sample Population Characteristics for Residency-Based Financial Aid Programs, separated by State and Cluster Analysis Results.

		Program Characteristics												Cluster Identity		
Program Name	State	City?	Early?	Committed?	Last Dollar?	Percentage?	Flat?	GPA?	ACT?	Income?	Select?	2-yr?	4-yr?	Ward	Avg.	Wgt. Avg.
Newark College Promise	NJ	Yes	Yes	No	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes	3	3	3
New Jersey Tuition Aid Grant	NJ	No	No	No	No	No	Yes	No	No	Yes	Yes	Yes	Yes	1	1	1
School Counts!:Carney's	NJ	Yes	No	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	3	3	3
School Counts!:Cumberland	NJ	Yes	No	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	3	3	3
Princeton Uniersity	NJ	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Legislative Lottery Scholarship/ 3% Bridge	NM	No	No	No	Yes	No	No	Yes	No	No	No	Yes	Yes	1	1	1
Govenrnor Quinn Millennium Scholarship	NV	No	No	No	Yes	No	No	Yes	No	No	No	Yes	Yes	1	1	1
Columbia University	NY	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Cornell University	NY	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
New York State TAP	NY	No	No	Yes	Yes	No	No	No	No	Yes	No	Yes	Yes	1	1	1
Rochester Promise	NY	Yes	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Say Yes to Education: Buffalo	NY	Yes	No	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes	3	3	3
Say Yes to Education: Syracuse	NY	Yes	No	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes	3	3	3
Vassar College	NY	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Blue and Gold Scholar Award	OH	No	No	Yes	Yes	No	No	Yes	No	Yes	Yes	No	Yes	2	2	2
Champion City Scholars Program	OH	Yes	Yes	No	Yes	No	No	Yes	No	Yes	Yes	Yes	No	3	3	3
Kenyon College	OH	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Miami Access Initiative	OH	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Montgomery Cty OH College Promise	OH	Yes	Yes	No	Yes	No	No	No	No	Yes	Yes	Yes	No	3	3	3
Oberlin College	OH	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Ohio College Opportunity Grant	OH	No	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
Oklahoma Promise	OK	No	Yes	Yes	Yes	No	No	Yes	No	Yes	No	Yes	Yes	1	1	1
Oklahoma Tuitoin Aid Grant	OK	No	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
Tulsa Achieves	OK	Yes	Yes	Yes	No	Yes	No	Yes	No	No	Yes	Yes	No	3	3	3
Bernard Daly Educational Fund	OR	Yes	No	No	Yes	No	No	No	No	No	Yes	Yes	Yes	3	3	3
Future Connect	OR	Yes	No	No	No	No	Yes	No	No	Yes	Yes	Yes	No	3	3	3
Oregon Opportunity Grant	OR	No	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
Oregon Promise	OR	No	No	Yes	Yes	No	No	Yes	No	No	No	Yes	No	1	1	1
Pathway Oregon	OR	No	No	No	Yes	No	No	Yes	No	Yes	Yes	No	Yes	2	2	2
50th Anniversary Scholars	PA	Yes	No	Yes	Yes	No	No	No	No	Yes	Yes	Yes	No	3	3	3
CORE Promise	PA	Yes	Yes	Yes	No	No	Yes	No	No	No	Yes	Yes	Yes	3	3	3
Haverford College	PA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Lafayette College	PA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Lehigh University	PA	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Philadelphia Education Fund	PA	Yes	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	3	3	3
Pittsburgh Promise	PA	Yes	No	Yes	No	Yes	No	Yes	No	No	No	Yes	Yes	3	3	3
Swathmore College	PA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
UPenn	PA	No	No	Yes	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
Brown University	RI	No	No	Yes	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
Crusade of Rhode Island	RI	No	Yes	Yes	No	No	Yes	No	No	No	No	Yes	Yes	1	1	1

Note. *City* signifies if the geographic region for eligibility is within a county or smaller. *Early* shows if students earn eligibility prior to entering high school. *Committed* signals if aid award is distributed to all eligible students. *Last Dollar*, *Percentage*, and *Flat* identify the aid distribution method. *GPA*, *ACT*, and *Income* identify if sub-qualifications are used for eligibility. *Select* determines if award is only redeemable at a select subset of institutions. *2-yr* and *4-yr* describe the institution type aid can be redeemed. Cluster Identity labels: 1=State-Based, 2=Institutional, and 3= Community-Sustained.

* denotes programs that are not placed in consistent groups across clustering methods.

Table 1. *cont*.

Sample Population Characteristics for Residency-Based Financial Aid Programs, separated by State and Cluster Analysis Results.

		Program Characteristics												Cluster Identity		
Program Name	State	City?	Early?	Committed?	Last Dollar?	Percentage?	Flat?	GPA?	ACT?	Income?	Select?	2-yr?	4-yr?	Ward	Avg.	Wgt. Avg.
South Dakota Jump Start Scholarship	SD	No	No	Yes	No	No	Yes	No	No	No	No	Yes	Yes	1	1	1
South Dakota Opportunity Scholarship	SD	No	No	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	1	1	1
Ayers Foundation Scholars Program	TN	Yes	Yes	Yes	No	No	Yes	No	No	No	No	Yes	Yes	3	3	3
Dyer County Promise Scholarship	TN	Yes	No	Yes	No	No	Yes	No	No	No	Yes	Yes	No	3	3	3
Educate and Grow	TN	Yes	Yes	Yes	Yes	No	No	No	No	No	ys	Yes	No	3	3	3
Opportunity Vanderbilt	TN	No	No	Yes	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
Tennessee Pledge	TN	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
tnAchieves (Knox Achieves)	TN	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
William Jennings Bryan Opportunity	TN	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Aggie Assurance	TX	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Bobcat Promise	TX	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Lamar Promise	TX	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Rice University	TX	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Rusk TJC Citizens Promise	TX	Yes	No	No	No	No	Yes	Yes	No	No	Yes	Yes	No	3	3	3
Sacred Heart University	TX	Yes	No	No	Yes	No	No	No	No	No	Yes	No	Yes	2	2	2
* TEXAS Grant	TX	No	No	No	No	No	Yes	No	No	Yes	No	No	Yes	1	1	2
UTEP Promise	TX	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
SLCC Promise	UT	Yes	No	Yes	Yes	No	No	No	No	Yes	Yes	Yes	No	3	3	3
Regent Scholarship	UT	No	No	No	No	No	Yes	Yes	Yes	No	No	Yes	Yes	1	1	1
Beacon of Hope	VA	Yes	No	No	No	No	Yes	Yes	No	No	No	Yes	Yes	3	3	3
Virginia Guaranteed Assistance	VA	No	No	Yes	Yes	No	No	Yes	No	Yes	No	Yes	Yes	1	1	1
William and Mary Promise/Gateway	VA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
13th Year Promise	WA	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	No	3	3	3
* College Success Foundation	WA	No	No	No	No	No	Yes	Yes	No	Yes	No	No	Yes	1	1	2
Husky Promise	WA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	2	2	2
Passport for Foster Youth Promise	WA	No	No	Yes	No	No	Yes	No	No	No	No	Yes	Yes	1	1	1
Seattle Promise	WA	No	No	Yes	Yes	No	No	No	No	Yes	Yes	Yes	No	1	1	1
Shoreline Scholars	WA	Yes	No	No	Yes	No	No	Yes	No	Yes	Yes	Yes	No	3	3	3
Washington College Bound Scholarship	WA	No	Yes	Yes	Yes	No	No	Yes	No	Yes	No	Yes	Yes	1	1	1
* WA State Need Grant	WA	No	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	2
Nicolet Promise	WI	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	No	3	3	3
Wisconsin Tuition Assistance Grant	WI	No	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	1	1	1
WITC Promise	WI	No	No	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	No	1	1	1
Hathaway Scholarship	WY	No	No	No	No	Yes	No	Yes	Yes	No	No	Yes	Yes	1	1	1
West Virginia Promise Scholarship	WV	No	No	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	1	1	1

Note. *City* signifies if the geographic region for eligibility is within a county or smaller. *Early* shows if students earn eligibility prior to entering high school. *Committed* signals if aid award is distributed to all eligible students. *Last Dollar*, *Percentage*, and *Flat* identify the aid distribution method. *GPA*, *ACT*, and *Income* identify if sub-qualifications are used for eligibility. *Select* determines if award is only redeemable at a select subset of institutions. *2-yr* and *4-yr* describe the institution type aid can be redeemed. Cluster Identity labels: 1=State-Based, 2=Institutional, and 3= Community-Sustained.

* denotes programs that are not placed in consistent groups across clustering methods.

Table 2.

Distribution Statistics of Sample Population of Residency-Based Financial Aid, separated by Ward Cluster Analysis Results

		City	Early	Commit	Percent	Last Dollar	Flat	GPA	Income	Select	2-yr	4-yr
Characteristic Total	n.	0	8	26	2	17	29	24	27	8	45	42
State-Based (Total)	n.	48	48	48	48	48	48	48	48	48	48	48
Percentage	%	0.0%	16.7%	54.2%	4.2%	35.4%	60.4%	50.0%	56.3%	16.7%	93.8%	87.5%
Characteristic Total	n.	10	1	50	0	70	2	7	57	72	0	37
Institutional No Loan (Total)	n.	72	72	72	72	72	72	72	72	72	72	72
Percentage	%	13.9%	1.4%	69.4%	0.0%	97.2%	2.8%	9.7%	79.2%	100.0%	0.0%	51.4%
Characteristic Total	n.	79	41	61	13	46	20	32	18	56	75	37
Community-Sustained (Total)	n.	79	79	79	79	79	79	79	79	79	79	79
Percentage	%	100.0%	51.9%	77.2%	16.5%	58.2%	25.3%	40.5%	22.8%	70.9%	94.9%	46.8%
Characteristic Total	n.	89	50	137	15	133	51	63	102	136	120	116
Sample Total	n.	199	199	199	199	199	199	199	199	199	199	199
Percentage	%	44.7%	25.1%	68.8%	7.5%	66.8%	25.6%	31.7%	51.3%	68.3%	60.3%	58.3%

Note. *City* signifies if the geographic region for eligibility is within a county or smaller. *Early* shows if students earn eligibility prior to entering high school. *Committed* signals if aid award is distributed to all eligible students. *Last Dollar*, *Percentage*, and *Flat* identify the aid distribution method. *GPA*, *ACT*, and *Income* identify if sub-qualifications are used for eligibility. *Select* determines if award is only redeemable at a select subset of institutions. *2-yr* and *4-yr* describe the institution type aid can be redeemed.

Table 3.

Dataset Characteristics for Sample Population of Community-Sustained Residency-Based Financial Aid Programs.

				Program Characteristics								
State	No. of Programs	Early	Commit	Percentage	Unmet Need	Flat	None	GPA	Income	Select Institutions	2-year alternatives	4-yr alternatives
Arkansas	5	2	5	1	2	2	3	2	0	3	5	2
Arizona	1	1	1	0	1	0	0	1	0	1	1	0
California	11	9	9	0	8	3	8	2	2	8	9	5
Colorado	2	1	2	0	1	1	0	2	2	1	2	1
Connecticut	1	1	1	1	0	0	0	1	0	0	1	1
Washington, DC	1	0	0	0	0	1	0	0	1	1	1	1
Florida	3	1	2	0	2	1	2	1	0	2	3	2
Illinois	6	4	5	2	3	1	4	2	0	5	6	1
Indiana	1	1	1	1	0	0	0	1	0	0	1	1
Kentucky	4	2	4	0	3	1	0	4	0	4	4	0
Maryland	1	1	1	0	1	0	1	0	0	1	1	0
Michigan	14	8	12	6	6	2	12	2	0	6	14	10
Minnesota	1	0	0	0	1	0	0	0	1	1	1	1
Missouri	1	0	1	0	1	0	0	1	0	0	1	0
North Carolina	1	1	1	0	1	0	0	1	1	1	1	0
New Jersey	4	1	2	0	4	0	0	4	2	4	3	2
New York	2	0	2	0	2	0	0	0	2	2	2	2
Ohio	2	2	0	0	1	1	0	1	2	2	2	1
Oklahoma	1	1	1	1	0	0	0	1	0	1	1	0
Oregon	2	0	0	0	1	1	1	0	1	2	2	1
Pennsylvania	5	2	4	1	2	2	2	2	2	3	4	4
Tennessee	4	3	4	0	2	2	4	0	0	3	4	1
Texas	1	0	0	0	0	1	0	1	0	1	1	0
Utah	1	0	1	0	1	0	0	0	1	1	1	0
Virginia	1	0	0	0	0	1	0	1	0	0	1	1
Washington	2	1	1	0	2	0	1	1	0	2	2	0
Wisconsin	1	0	1	0	1	0	0	1	1	1	1	0
Total	79	42	61	13	46	20	38	32	18	56	75	37

Note. Community-sustained residency-Based aid programs are considered to be any program with Ward Cluster Analysis results= 3. *Early* shows if students earn eligibility prior to entering high school. *Committed* signals if aid award is distributed to all eligible students. *Last Dollar*, *Percentage*, and *Flat* identify the aid distribution method. *None* identifies that no sub-qualifications are used. *GPA* and *Income* identify if sub-qualifications are used for eligibility. *Select* determines if award is only redeemable at a select subset of institutions. *2-yr* and *4-yr* describes the institution type aid can be redeemed.

Table 4.
Descriptive Statistics of Macon County, Illinois

Descriptive Category	2010	2011	2012	2013	2014	2015
Population Statistics:						
Population (16 yr.+)	88,816	88,847	87,453	87,737	86,939	85,920
Civilian Labor Force	53,170	53,982	56,707	55,553	54,684	51,329
Unemployed (%)	7.6%	10.1%	13.1%	11.2%	9.9%	6.5%
Income and Poverty Statistics:						
Median Household Income	$40,919	$44,415	$44,533	$45,957	$47,574	$48,040
Mean Household Income	$53,597	$60,813	$58,049	$62,101	$63,140	$66,687
Per Capita Income	$22,688	$25,244	$24,756	$26,148	$26,459	$28,185
Families below Poverty Level (%)	12.6%	9.5%	17.2%	15.3%	11.4%	13.8%
w/ children 18yr or younger (%)	22.3%	16.8%	35.2%	24.8%	20.2%	25.6%
w/ children 5 years or younger (%)	26.0%	17.7%	36.8%	41.3%	26.8%	30.3%
Highest Level of Education (25 yrs ≤):						
High School diploma	48.0%	47.4%	47.1%	46.8%	46.4%	45.9%
Associate’s degree	6.2%	7.1%	6.6%	6.6%	6.7%	8.0%
Bachelor’s degree	13.6%	14.2%	14.6%	14.7%	15.4%	15.2%

Source: RCC Yearbook (n.d.)

Table 5.

Major Employers in Macon County in 2015, separated by Industry Type, Company Name, and Number of Employees

Industry Type and Company Name	Employees
Manufacturing	
Archer Daniels Midland	4,040
Caterpillar	3,292
Tate & Lyle/A.E. Staley	634
Mueller	455
Akorn Incorporated	300
Macon Resources, Inc	285
Stratas Foods	200
PPG Industries, Inc.	175
Christy Foltz, Inc.	150
International Control Services	141
Service, Support & Transportation	
Ameren Illinois	512
Norfolk Southern Corp.	500
Kelly Group	450
Bodine Electric Of	400
All Tri-R, Inc.	300
Centurion Industries, Inc.	300
Bodine Services Of Decatur, Inc.	200
McLeod Express	130
Myers Co., The L. E	110
McMillen Enterprises, Inc., R. D.	100
Office/Professional – Public	
Decatur Public School District	1,500
Macon County	545
City of Decatur	506
Richland Community College	450
Mt Zion School District	240
IL Dept of Corrections	210
Office/Professional – Private	
Decatur Memorial Hospital	2,374
St. Mary's Hospital	1,136
Millikin University	627
Addus Health Care	225
Decatur Conference Center & Hotel	165
Busey Bank	120
Business Center of Decatur	100
Soy Capital Bank & Trust Co	100

Source: RCC Yearbook (n.d.)

Table 6.
Richland Community College In-District High Schools and Counties Represented, separated by Carroll Scholarship Eligibility and Public/Private affiliation

Scholarship Eligibility for In-District High Schools and High School Type	Counties represented by High School District
Carroll Eligible High School:	
Meridian High School	Macon, Christian
Non-Eligible Public High Schools:	
Argenta-Oreana	Macon, Dewitt
Central A& M	Christian, Shelby
Cerro Gordo	Macon, Piatt
Clinton	Macon, DeWitt, Logan
Decatur Eisenhower	Macon
Decatur MacArthur	Macon
Maroa-Forsyth	Macon, DeWitt
Mt. Zion	Macon, Moultrie
Sangamon Valley	Macon, Sangamon, Christian
Warrensburg-Latham	Macon, Logan
Non-Eligible Private High Schools:	
Decatur Christian	n.a.
Lutheran School Association	n.a.
St. Teresa	n.a.

Note. The 13 non-Carroll Scholarship high schools are given a unique random id number in the dataset used for this research. The random id numbers used for the dataset are, in numeric order: 440, 758, 1936, 5192, 5502, 5620, 5623, 5625, 5627, 5628, 6629, 20145, and 121442. I am not able to align the specific high schools to random id numbers.

Table 7.

Enrollment Size, Demographics, and Secondary School Characteristics of Richland Community College Enrolled Students, separated by Carroll Scholarship Eligible High Schools and Senior Class Year

Characteristic	School		Pre-Carroll 2010	Pre-Carroll 2011	Pre-Carroll 2012	Post-Carroll 2013	Post-Carroll 2014	Post-Carroll 2015
High School Senior Class Size, No. and Percent of Class Size Enrolled at RCC	Meridian	n.	73	79	73	73	75	75
		n.	23	37	15	26	37	40
		%	31.5%	46.8%	20.5%	35.6%	49.3%	53.3%
	In-District	n.	1,095	1,155	1,061	975	938	939
		n.	307	303	274	250	277	238
		%	28.0%	26.2%	25.8%	25.6%	29.5%	25.3%
No. and Percent of RCC Enrolled: Male	Meridian	n.	+	19	+	12	16	27
		%	39.1%	51.4%	26.7%	46.2%	43.2%	67.5%
	In-District	n.	131	145	133	117	123	103
		%	42.7%	47.9%	48.5%	46.8%	44.4%	41.5%
No. and Percent of RCC Enrolled: Female	Meridian	n.	14	18	11	14	21	13
		%	60.9%	48.7%	73.3%	53.9%	56.8%	32.5%
	In-District	n.	176	158	140	133	154	145
		%	57.3%	52.2%	51.1%	53.2%	55.6%	58.5%
No. and Percent of RCC Enrolled: White	Meridian	n.	22	35	12	24	36	37
		%	96.0%	94.6%	80.0%	92.3%	97.3%	92.5%
	In-District	n.	251	249	220	199	219	199
		%	81.8%	82.2%	80.3%	79.3%	79.1%	80.2%
Avg. HS GPA, ACT score, and No. of Math courses taken for RCC Enrolled Students	Meridian	HS GPA	2.86	2.71	2.93	2.81	2.87	2.7
		ACT	20.89	19.19	20.08	19.15	19.75	21.26
		Math	1.39	1.41	1.4	1.62	1.62	1.83
	In-District	HS GPA	3.13	3.11	3.2	3.16	3.26	3.24
		ACT	20.32	19.82	19.85	20.09	20.08	19.23
		Math	1.76	1.81	1.79	1.81	1.91	1.85

Note. In-District demographics represent the combined numbers for all 13 non-Meridian High Schools in the sample. Demographics for all other race and ethnicity categories are suppressed because of the small number of Meridian students in those categories. Average ACT score is calculated from the scores reported to RCC. Average Math courses taken is the number of mathematics courses taken beyond Illinois' graduation requirement.
+ signifies that the sample size is smaller than 10 students.

Table 8.

Dataset Population, separated by Carroll Scholarship High School Eligibility and Number of Students Registered in time periods before and after the Carroll Scholarship announcement

	Strictly took courses in the Pre-Carroll Scholarship Semesters	Registered in both pre- and post-Carroll Scholarship semesters	Strictly took courses in the post-Carroll Scholarship semesters
Students who graduated from Meridian High School N=178	Students who would be eligible, but did not register for Richland courses in the semesters after the Carroll Scholarship creation. N= 39	Are initially ineligible for the Carroll scholarship because they began taking Richland courses in a time period prior to the scholarship creation, but became eligible and continued coursework in the post-Carroll Scholarship creation semesters. N= 36	Are eligible to receive the Carroll Scholarship in all semesters registered at Richland. N= 103
Students who graduated from the remaining 13 in-district high schools N=1,659	Did not attend the eligible high school and did not register for Richland courses in the semesters after the Carroll scholarship creation. N= 489	Did not attend the eligible high school, but took Richland courses in the semesters before and after the Carroll Scholarship creation. N= 395	Did not attend the eligible high school, but took all Richland courses in the semesters after the Carroll Scholarship creation. N= 775

Note. The dataset constructed for this research includes students who transitioned to Richland immediately following high school completion. A fourth potential group exists of students who delayed enrollment. The fourth group of students is omitted from this research.

Table 9.

OLS Regression naïve Models for Prior Year trends of High School Grade Point Average (HS GPA): MERIDIAN student treatment condition: Pre-Carroll Scholarship Senior Class Time Periods (2010-2012): Halved based on High School Grade Point Average

Model (Std. Error)	*H.S. GPA*	
	H.S. GPA (1.085-3.170)	H.S. GPA (3.171-5.000)
	OLS	OLS
	(1)	(2)
MERIDIAN	-0.0314	-0.0706
	(0.0788)	(0.0791)
Dual Credit Enrollee	0.0331	0.0863**
	(0.0433)	(0.0412)
Male	-0.0830**	-0.104***
	(0.0381)	(0.0367)
White	0.300**	-0.0511
	(0.136)	(0.150)
African-American	-0.0389	-0.165
	(0.146)	(0.186)
Hispanic	0.0900	-0.0861
	(0.177)	(0.261)
Two or More Identified	xx	-0.116
	xx	(0.172)
Constant	2.192***	3.545***
	(0.152)	(0.165)
Senior Class Year Fixed Effects	Yes	Yes
Non-Meridian High School Dummy	Yes	Yes
N. Treatment (Meridian)	48	23
N. Control (In-District)	387	401
Observations	435	424
R-squared	0.209	0.260

Note. Robust standard errors in parentheses. The naïve regressions restrict the data to include only students that graduated in the pre-Carroll Scholarship time periods, 2010-2012. *MERIDIAN* is a dummy variable. Non-Dual Credit, Female, and All Other are the omitted variable categories. 2010 is the omitted Senior Class Year Fixed Effect category. School ID Number 5625 is the omitted Non-Meridian High School dummy variable.
*** p<0.01, ** p<0.05, * p<0.1.

Table 10.

OLS Regression naïve Models for Associates Degree Path and Transferable Degree Path: MERIDIAN student treatment condition: Pre-Carroll Scholarship Academic Semester Time Periods (Fall 2010-Summer 2013): Halved based on High School Grade Point Average

	Curricular Path			
	Associates Degree Path		*Transferable Degree Path*	
Models	H.S. GPA (1.085-3.170)	H.S. GPA (3.171-5.000)	H.S. GPA (1.085-3.170)	H.S. GPA (3.171-5.000)
(Std. Error)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS
MERIDIAN	-0.0397	-0.0278	-0.0816	0.0208
	(0.124)	(0.117)	(0.0822)	(0.0138)
Dual Credit Enrollee	0.0677	-0.0563	0.0334	0.0706**
	(0.0724)	(0.0605)	(0.0374)	(0.0319)
Male	-0.0812	-0.0795	-0.0675**	0.0271
	(0.0668)	(0.0609)	(0.0340)	(0.0241)
White	-0.390***	0.775***	-0.0109	-0.0507
	(0.0914)	(0.0767)	(0.0364)	(0.0332)
African-American	-0.223**	0.638**	0.0162	-0.0163
	(0.105)	(0.259)	(0.0500)	(0.0444)
Hispanic	-0.0537	1.202***	0.145	-0.111**
	(0.168)	(0.192)	(0.0917)	(0.0562)
Two or More Identified	-0.286	0.625***	0.0907	-0.00374
	(0.186)	(0.223)	(0.0651)	(0.0440)
Constant	0.968***	0.173*	0.946***	0.986***
	(0.186)	(0.103)	(0.0907)	(0.0310)
Semester Fixed Effects	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	21	13	21	13
N. Control (In-District)	207	204	207	204
Observations	228	217	228	217
R-squared	0.070	0.155	0.066	0.064

Note. Robust standard errors in parentheses. The naïve regressions restrict the data to include only students that graduated in the pre-Carroll Scholarship time periods, 2010-2012. *MERIDIAN* is a dummy variable. Non-Dual Credit, Female, and All Other are the omitted variable categories.
*** p<0.01, ** p<0.05, * p<0.1.

Table 11.

OLS and Logistic Regression predictive Difference-in-Difference Models for Mean High School Grade Point Average: Carroll Scholarship Eligibility Treatment Condition: separated by High School Grade Point Average Quartiles

	H.S. GPA							
	Q1		Q2		Q3		Q4	
Models	(1.085-2.720)		(2.722-3.200)		(3.204-3.701)		(3.710-5.000)	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
MERIDIAN x POST	0.0424	1.246	-0.0352	0.823	-0.0259	0.853	-0.0310	0.814
	(0.0286)	(0.252)	(0.0370)	(0.178)	(0.0290)	(0.143)	(0.0195)	(0.121)
MERIDIAN	0.261***	4.340***	-0.0481*	0.804	-0.0380	0.809	-0.222***	0.165***
	(0.0279)	(0.906)	(0.0238)	(0.125)	(0.0247)	(0.114)	(0.0210)	(0.0246)
POST	-0.696***	4.02e-07***	-0.219**	6.62e-06***	0.00264	5.85e-05***	0.375***	0.00486***
	(0.0339)	(4.57e-07)	(0.0768)	(4.74e-06)	(0.0683)	(6.78e-05)	(0.0594)	(0.00546)
Dual Credit Enrollee	-0.0263	0.822	-0.0140	0.912	0.0403	1.267	0.0762**	1.763***
	(0.0280)	(0.159)	(0.0315)	(0.178)	(0.0303)	(0.236)	(0.0313)	(0.304)
Male	0.0765***	1.639***	0.0468**	1.321***	-0.0259	0.863	-0.111***	0.437***
	(0.0125)	(0.105)	(0.0171)	(0.137)	(0.0215)	(0.110)	(0.0146)	(0.0382)
White	0.0207	1.114	-0.0310	0.849	0.00446	1.005	0.0372	1.247
	(0.0619)	(0.557)	(0.0976)	(0.439)	(0.0705)	(0.415)	(0.0555)	(0.483)
African-American	0.224**	2.996**	-0.0835	0.626	-0.0630	0.577	-0.0514	0.405
	(0.0787)	(1.609)	(0.111)	(0.375)	(0.0635)	(0.253)	(0.0656)	(0.225)
Hispanic	0.232	3.096	-0.145	0.390	-0.0441	0.742	0.0447	1.270
	(0.222)	(3.442)	(0.131)	(0.356)	(0.144)	(0.680)	(0.0618)	(0.596)
Two or More Identified	0.0749	1.574	-0.0509	0.742	-0.0344	0.766	0.0138	0.996
	(0.112)	(1.137)	(0.144)	(0.598)	(0.0800)	(0.426)	(0.0686)	(0.538)
Constant	0.815***	345,611***	0.529***	65,525***	0.237**	5,465***	-0.0768	91.96***
	(0.0499)	(392,519)	(0.136)	(50,631)	(0.102)	(7,173)	(0.0823)	(110.2)
Non-Meridian High School Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Senior Class Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	178	178	178	178	178	178	178	178
N. Control (In-District)	1,658	1,419	1,658	1,658	1,658	1,658	1,658	1,658
Observations	1,836	1,597	1,836	1,836	1,836	1,836	1,836	1,836
R-squared (Psuedo)	0.145	0.103	0.047	0.048	0.036	0.036	0.247	0.227

Note. Standard errors clustered by high school. *MERIDIAN* is a dummy variable. School ID Number 5625 is the omitted Non-Meridian High School dummy variable. Non-Dual Credit, Female, and Non-White are the omitted variable categories. Logistic models report Odds Ratio coefficient results. Logistic models report Pseudo R-squared. *** p<0.01, ** p<0.05, * p<0.1.

Table 12.

OLS and Logistic Regression predictive Difference-in-Difference Models for Pell Grant Receipt: Carroll Scholarship Eligibility Treatment Condition

Models (Std. Error)	*Pell Grant Recipient* (1) OLS	(2) Logistic
MERIDIAN x POST	0.0223	1.121
	(0.0160)	(0.103)
MERIDIAN	-0.0906***	0.655***
	(0.0220)	(0.0650)
POST	0.0428**	1.261**
	(0.0163)	(0.118)
Dual Credit Enrollee	-0.150***	0.472***
	(0.0348)	(0.0684)
Male	-0.0670***	0.698***
	(0.0161)	(0.0652)
White	0.102*	1.692*
	(0.0499)	(0.514)
African-American	0.312***	4.192***
	(0.0619)	(1.437)
Hispanic	0.312***	4.582***
	(0.0864)	(1.812)
Two or More Identified	0.247**	3.204**
	(0.107)	(1.693)
Constant	0.386***	0.604
	(0.0567)	(0.196)
Non-Meridian High School Dummy	Yes	Yes
Year Fixed Effects	Yes	Yes
HS_GPA Quartile Dummy	No	Yes
N. Treatment (Meridian)	454	454
N. Control (In-District)	3,950	3,950
Observations	4,404	4,405
R-squared (Psuedo)	0.106	0.087

Note. Standard errors clustered by high school. *MERIDIAN* is a dummy variable. School ID Number 5625 is the omitted Non-Meridian High School dummy variable. Quartile 1 is the omitted HS_GPA Quartile dummy variable. Non-Dual Credit, Female, and Non-White are the omitted variable categories. Logistic models report Odds Ratio coefficient results. Logistic models report Pseudo R-squared.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13.

First-Year Student Financial Aid Information, separated by Carroll Scholarship High School Eligibility and Senior Class Year

			Pre-Carroll			Post-Carroll		
			2010	2011	2012	2013	2014	2015
Filed FAFSA	Meridian	n.	14	24	12	26	37	38
		%	60.9%	64.9%	80.0%	100.0%	100.0%	95.0%
	In-District	n.	219	230	213	201	235	218
		%	71.3%	75.9%	77.7%	80.4%	84.8%	87.9%
Avg. EFC	Meridian	$	7,703	11,199	7,967	12,266	14,420	9,851
		$	8,014	6,062	8,987	8,990	9,331	8,413
Avg. Student Income	In-District	$	2,572	1,300	1,256	4,313	1,487	1,643
		$	2,866	2,144	1,933	2,590	2,471	2,877
Grant Aid Awards	Meridian	%	26.1%	16.2%	40.0%	26.9%	16.2%	25.0%
		$	1,219	687	1,029	666	750	653
	In-District	%	23.8%	28.1%	18.2%	26.0%	26.0%	27.4%
		$	1,098	808	755	813	822	816
Pell Grant Awards	Meridian	%	39.1%	37.8%	53.3%	38.5%	40.5%	47.5%
		$	3,688	2,447	3,980	4,217	2,871	3,505
	In-District	%	38.1%	46.5%	38.3%	39.6%	47.7%	49.2%
		$	3,688	2,447	3,980	4,217	2,871	3,505
Scholarship Aid Awards	Meridian	%	17.4%	29.7%	33.3%	11.5%	16.2%	27.5%
		$	1,279	1,275	768	1,637	1,734	981
	In-District	%	23.1%	23.8%	29.9%	34.4%	41.5%	39.1%
		$	1,484	1,344	1,366	1,312	1,387	1,496
Tuition Waiver Awards	Meridian	%	17.4%	16.2%	40.0%	3.8%	5.4%	25.0%
		$	1,672	1,585	1,688	574	1,142	404
	In-District	%	15.6%	16.2%	19.7%	22.8%	23.5%	39.5%
		$	1,671	1,730	1,755	2,105	2,269	1,623

Note. In-District calculations represent the combined numbers for all 13 non-Meridian High Schools in the sample. RCC does not use a formal definition for categorizing financial aid programs and awards. All calculations are based on the category where RCC aligned the specific award. All financial aid calculations exclude the Carroll Scholarship award. Average award value is calculated using only students awarded that specific type of aid. Average EFC and Student Income is calculated using FAFSA application results and omits students who did not file FAFSA. Grant Aid Awards excludes Pell Grant calculations.

Table 14.
Average Carroll Scholarship Distribution Received; per Meridian student; separated by Senior Class and Academic Year Received

Average Carroll Scholarship Award		2010	2011	2012	2013	2014	2015
Average Award, by Senior Class	n.	+	+	+	15	28	24
	$.	2,040	2,431	1,680	4,402	3,750	2,125
Average Award, by Academic Year	n.	n.a.	n.a.	n.a.	27	49	95
	$.	n.a.	n.a.	n.a.	1,825	1,854	1,246

Note. Average Carroll Scholarship Award by Senior Class, identifies the Senior Class year for the student receiving Carroll funding. This does not align with the postsecondary academic year the students received the award.
+ signifies a sample size smaller than 10 students.

Table 15.

First-Year Student Postsecondary Outcomes, separated by Carroll Scholarship High School Eligibility and Senior Class Year

Student Outcomes	School		Pre-Carroll			Post-Carroll		
			2010	2011	2012	2013	2014	2015
Students Enrolled, Students Enrolled Full-Time (12+ cr. hr.), and percent Full-Time	Meridian	n.	23	37	15	26	37	40
		n.	15	14	+	17	19	21
		%	65.2%	37.8%	40.0%	65.4%	51.4%	52.5%
	In-District	n.	307	303	274	250	277	248
		n.	161	143	136	127	146	128
		%	52.4%	47.2%	49.6%	50.8%	52.7%	51.6%
Credit Hours Attempted, Credit Hours Earned, and Credit Hour Success Rate	Meridian	n.	23.5	22.7	21.5	25.3	22.9	23.8
		n.	18	16.4	16.5	22.7	19.8	20.2
		%	76.6%	72.2%	76.7%	89.7%	86.5%	84.9%
	In-District	n.	23	21.8	22.7	23.1	23.4	23.7
		n.	18.8	16.9	18.3	19.3	19.7	20.2
		%	81.7%	77.5%	80.6%	83.5%	84.2%	85.2%
Failed a course	Meridian	n.	+	11	+	+	16	10
		%	30.4%	29.7%	20.0%	7.7%	43.2%	25.0%
	In-District	n.	94	108	88	81	85	74
		%	30.6%	35.6%	32.1%	32.4%	30.7%	29.8%
Withdrew from a course	Meridian	n.	13	28	+	11	21	24
		%	56.5%	75.7%	40.0%	42.3%	56.8%	60.0%
	In-District	n.	185	180	152	134	153	128
		%	60.3%	59.4%	55.5%	53.6%	55.2%	51.6%

Note. In-District calculations represent the combined numbers for all 13 non-Meridian High Schools in the sample. Credit Hour Success Rate is the total credit hours attempted in a semester divided by the number of credit hours that did not result in a failing letter grade (F) or a course withdrawal (WD).
+ signifies a sample size smaller than 10 students

Table 16.

Difference-in-Difference Models for Mean High School Grade Point Average: Carroll Scholarship Eligibility Treatment Condition: separated by High School Grade Point Average Quartiles

Models (Std. Error)	Full Sample		H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
	Student Secondary School Characteristics H.S. GPA					
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
MERIDIAN x POST	-0.0766*	-0.00134	-0.0218	-0.0132	-0.0539***	0.193***
	(0.0409)	(0.0107)	(0.0206)	(0.0149)	(0.0178)	(0.0232)
MERIDIAN	-0.489***	-0.0500***	-0.0404	-0.0303	-0.0665***	-0.125***
	(0.0404)	(0.0132)	(0.0485)	(0.0206)	(0.0189)	(0.0242)
POST	0.0464	0.0427*	0.0784***	-0.0177	0.00135	0.112**
	(0.0391)	(0.0203)	(0.0200)	(0.0205)	(0.0359)	(0.0473)
Dual Credit Enrollee	0.176***	0.0513***	0.111***	0.00319	0.00713	0.0305
	(0.0372)	(0.0140)	(0.0344)	(0.0165)	(0.0215)	(0.0454)
Male	-0.227***	-0.0293**	-0.0376	0.00850	-0.0172	-0.0652**
	(0.0159)	(0.0128)	(0.0257)	(0.0131)	(0.0122)	(0.0264)
White	0.0330	-0.00853	0.134	-0.107***	0.0949*	-0.133**
	(0.101)	(0.0372)	(0.125)	(0.0185)	(0.0484)	(0.0578)
African-American	-0.351**	-0.105*	0.0287	-0.129***	0.0241	-0.225***
	(0.119)	(0.0502)	(0.113)	(0.0226)	(0.0920)	(0.0710)
Hispanic	-0.126	-0.0144	0.103	-0.195	0.00490	0.0363
	(0.209)	(0.0632)	(0.161)	(0.111)	(0.0467)	(0.155)
Two or More Identified	-0.108	-0.0533**	0.0916	-0.175***	0.200**	-0.212**
	(0.138)	(0.0201)	(0.0669)	(0.0424)	(0.0733)	(0.0761)
Constant	3.264***	2.276***	2.094***	3.047***	3.334***	4.007***
	(0.0844)	(0.0586)	(0.112)	(0.0147)	(0.0593)	(0.0371)
Non-Meridian High School Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
HS_GPA Quartile Dummy	No	Yes	No	No	No	No
N. Treatment (Meridian)	168	168	74	42	40	12
N. Control (In-District)	1,517	1,517	351	380	378	408
Observations	1,685	1,685	425	422	418	420
R-squared	0.381	0.891	0.135	0.111	0.087	0.286

Note. Standard errors clustered by high school. *MERIDIAN* is a dummy variable. School ID Number 5625 is the omitted Non-Meridian High School dummy variable. Quartile 1 is the omitted HS_GPA Quartile dummy variable. Non-Dual Credit, Female, and All Other are the omitted variable categories. The models measure the Intention to Treat (ITT) because each member of the treatment group is receiving information on postsecondary affordability, but is not necessarily receiving Carroll Scholarship funding.
*** p<0.01, ** p<0.05, * p<0.1.

Table 17.

Difference-in-Difference Models for Postsecondary Credit Hours Attempted at Richland: Carroll Scholarship Eligibility Treatment Condition: separated by High School Grade Point Average Quartiles

	Postsecondary Outcomes Credit Hours: Attempted				
Models (Std. Error)	Full Sample	H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
MERIDIAN x POST	1.149**	0.550	0.331	2.472**	3.515***
	(0.513)	(0.756)	(1.028)	(1.051)	(0.889)
Other Aid Amount ($100)	0.234***	0.146***	0.197***	0.240***	0.303***
	(0.00998)	(0.0188)	(0.0216)	(0.0210)	(0.0169)
Pell Grant Recipient	-0.526**	-0.775*	-0.838*	-0.647	-0.00699
	(0.239)	(0.437)	(0.484)	(0.518)	(0.469)
Pell Grant Amount ($100)	0.199***	0.243***	0.229***	0.207***	0.115***
	(0.0108)	(0.0187)	(0.0221)	(0.0247)	(0.0213)
Constant	5.018***	4.987***	5.976***	5.039***	4.082***
	(0.391)	(0.685)	(0.908)	(0.721)	(0.833)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
HS_GPA Quartile Dummy	No	No	No	No	No
N. Treatment (Meridian)	774	320	191	178	58
N. Control (In-District)	7,095	1,574	1,679	1,676	1,812
Number of id	1,837	496	409	392	389
Observations	7,869	1,894	1,870	1,854	1,870
R-squared	0.551	0.510	0.497	0.563	0.671

Note. Robust standard errors in parentheses. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. Student and Semester fixed effects allow Meridian students to switch from the control group to the treatment group in the time period after the Carroll Scholarship introduction. This aspect of the DID model helps avoid contamination both groups. The models measure the Intention to Treat (ITT) because each member of the treatment group is receiving information on postsecondary affordability, but is not necessarily receiving Carroll Scholarship funding.

*** p<0.01, ** p<0.05, * p<0.1

Table 18.

Difference-in-Difference Models for Postsecondary Credit Hours Earned at Richland: Carroll Scholarship Eligibility Treatment Condition: separated by High School Grade Point Average Quartiles

	Postsecondary Outcomes				
	Credit Hours: Earned				
Model	Full Sample	H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
(Std. Error)	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
MERIDIAN x POST	1.870***	0.816	2.000*	2.481**	3.913***
	(0.492)	(0.618)	(1.088)	(1.034)	(0.984)
Other Aid Amount ($100)	0.223***	0.107***	0.180***	0.222***	0.307***
	(0.0107)	(0.0197)	(0.0222)	(0.0218)	(0.0186)
Pell Grant Recipient	-1.300***	-2.054***	-0.880*	-1.892***	-0.185
	(0.259)	(0.471)	(0.483)	(0.609)	(0.500)
Pell Grant Amount ($100)	0.192***	0.248***	0.197***	0.233***	0.0911***
	(0.0120)	(0.0187)	(0.0234)	(0.0308)	(0.0233)
Constant	5.215***	4.833***	6.268***	5.166***	4.594***
	(0.399)	(0.662)	(0.907)	(0.719)	(0.905)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	774	320	191	178	58
N. Control (In-District)	7,095	1,574	1,679	1,676	1,812
Number of id	1,837	496	409	392	389
Observations	7,869	1,894	1,870	1,854	1,870
R-squared	0.426	0.324	0.367	0.471	0.588

Note. Robust standard errors in parentheses. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. Standard errors for Other Aid Award and Pell Grant Amount are not adjusted. Student and Semester fixed effects allow Meridian stuents to switch from the control group to the treatment group in the time period after the Carroll Scholarship introduction. This aspect of the DID model helps avoid contamination both groups. The models measure the Intention to Treat (ITT) because each member of the treatment group is receiving information on postsecondary affordability, but is not necessarily receiving Carroll Scholarship funding.
*** p<0.01, ** p<0.05, * p<0.1.

Table 19.

Difference-in-Difference Models for Postsecondary Credit Hours Withdrawn at Richland: Carroll Scholarship Eligibility Treatment Condition: separated by High School Grade Point Average Quartiles

Model (Std. Error)	*Postsecondary Outcomes Credit Hours: Withdrawn*				
	Full Sample	H.S. GPA: Q1 (1.085-2.720)	H.S. GPA: Q2 (2.722-3.200)	H.S. GPA: Q3 (3.204-3.701)	H.S. GPA: Q4 (3.710-5.000)
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
MERIDIAN x POST	-0.690**	-0.399	-1.501**	-0.0705	-0.173
	(0.316)	(0.498)	(0.711)	(0.559)	(0.227)
Other Aid Amount ($100)	8.57E-03	0.0352**	0.0173	0.0131	-3.59E-03
	(6.04e-03)	(0.0162)	(0.0166)	(0.0116)	(9.63e-03)
Pell Grant Recipient	0.692***	1.178***	0.0447	0.957**	0.199
	(0.202)	(0.425)	(0.413)	(0.469)	(0.243)
Pell Grant Amount ($100)	7.45E-03	-4.69E-03	0.0287	-0.0169	0.0197
	(0.0101)	(0.0196)	(0.0198)	(0.0250)	(0.0160)
Constant	-0.149	0.0862	-0.273	0.0912	-0.518
	(0.201)	(0.437)	(0.454)	(0.318)	(0.447)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	774	320	191	178	58
N. Control (In-District)	7,095	1,574	1,679	1,676	1,812
Number of id	1,837	496	409	392	389
Observations	7,869	1,894	1,870	1,854	1,870
R-squared	0.041	0.073	0.057	0.041	0.037

Note. Robust standard errors in parentheses. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. Student and Semester fixed effects allow Meridian students to switch from the control group to the treatment group in the time period after the Carroll Scholarship introduction. This aspect of the DID model helps avoid contamination both groups. The models measure the Intention to Treat (ITT) because each member of the treatment group is receiving information on postsecondary affordability, but is not necessarily receiving Carroll Scholarship funding.

*** p<0.01, ** p<0.05, * p<0.1.

Table 20.

Difference-in-Difference Models for Postsecondary Credit Hours Failed at Richland: Carroll Scholarship Eligibility Treatment Condition: separated by High School Grade Point Average Quartiles

Model (Std. Error)	*Postsecondary Outcomes Credit Hours: Failed*				
	Full Sample	H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
MERIDIAN x POST	-0.0872	-0.562	-0.261	0.650***	0.106
	(0.231)	(0.511)	(0.208)	(0.241)	(0.152)
Other Aid Amount ($100)	3.87E-03	5.12E-03	0.0114	2.45E-03	7.33E-03
	(3.51e-03)	(0.0132)	(8.55e-03)	(4.34e-03)	(4.73e-03)
Pell Grant Recipient	0.120	0.0381	-0.109	0.0908	0.435**
	(0.113)	(0.300)	(0.212)	(0.133)	(0.170)
Pell Grant Amount ($100)	0.0272***	0.0486***	0.0267**	7.22E-03	8.69E-03
	(6.28e-03)	(0.0153)	(0.0128)	(7.96e-03)	(9.10e-03)
Constant	0.0271	0.200	-0.0438	0.100	-0.122
	(0.0987)	(0.222)	(0.218)	(0.155)	(0.185)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	774	320	191	178	58
N. Control (In-District)	7,095	1,574	1,679	1,676	1,812
Number of id	1,837	496	409	392	389
Observations	7,869	1,894	1,870	1,854	1,870
R-squared	0.027	0.052	0.023	0.032	0.042

Note. Robust standard errors in parentheses. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. Student and Semester fixed effects allow Meridian students to switch from the control group to the treatment group in the time period after the Carroll Scholarship introduction. This aspect of the DID model helps avoid contamination both groups. The models measure the Intention to Treat (ITT) because each member of the treatment group is receiving information on postsecondary affordability, but is not necessarily receiving Carroll Scholarship funding.
*** p<0.01, ** p<0.05, * p<0.1.

Table 21.

Difference-in-Difference Models for Postsecondary Credit Hours Attempted at Richland: Received Carroll Scholarship Funding Treatment Condition: separated by High School Grade Point Average Quartiles

Model (Std. Error)	*Postsecondary Outcomes Credit Hours: Attempted*				
	Full Sample	H.S. GPA: Q1 (1.085-2.720)	H.S. GPA: Q2 (2.722-3.200)	H.S. GPA: Q3 (3.204-3.701)	H.S. GPA: Q4 (3.710-5.000)
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Carroll Scholarship Recipient	3.973***	3.983***	3.604***	5.209***	0.267
	(0.367)	(0.569)	(0.709)	(0.769)	(1.097)
Other Aid Amount ($100)	0.181***	0.152***	0.109**	0.260***	0.320***
	(0.0253)	(0.0502)	(0.0448)	(0.0408)	(0.0680)
Pell Grant Recipient	-0.823	0.915	-3.619***	-1.321	-3.341
	(0.531)	(0.735)	(0.986)	(1.292)	(2.168)
Pell Grant Amount ($100)	0.181***	0.130***	0.359***	0.137**	0.117
	(0.0250)	(0.0359)	(0.0389)	(0.0688)	(0.100)
Dual Credit Enrollee	0.796**	1.408***	-2.251***	-2.506***	-1.454
	(0.322)	(0.469)	(0.746)	(0.901)	(1.398)
H.S. GPA	0.628***	1.368***	3.291	-2.739	-4.855**
	(0.222)	(0.478)	(2.049)	(1.793)	(1.801)
Male	0.826***	0.758*	1.496***	0.314	1.715
	(0.267)	(0.439)	(0.517)	(0.547)	(1.221)
White	0.348	-0.562	-1.116	3.613***	-3.273
	(0.509)	(0.826)	(1.266)	(1.291)	(2.254)
Constant	2.504**	0.854	-0.621	13.71**	31.65***
	(1.111)	(1.886)	(5.774)	(6.418)	(9.825)
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Carroll)	227	107	56	50	14
N. Control (No Carroll)	520	213	135	128	44
Observations	747	320	191	178	58
R-squared	0.472	0.424	0.524	0.656	0.792

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. Non-Dual Credit, Female, and Non-White are the omitted variable categories. The treatment and control groups consist of Meridian students exclusively. *Carroll Scholarship Recipient* treatment is a binary measure identifying whether a student actually received Carroll Scholarship funds (Yes, *Carroll Scholarship Recipient*= 1, If a student does not receive a Carroll Scholarship, *Carroll Scholarship Recipient*= 0). Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards. The models measure the Average Treatment Effect (ATE) because each member of the treatment group is receiving Carroll Scholarship funding, not just information on postsecondary affordability.

*** p<0.01, ** p<0.05, * p<0.1.

Table 22.
Difference-in-Difference Models for Postsecondary Credit Hours Attempted at Richland: Amount of Carroll Scholarship Received Treatment Condition: separated by High School Grade Point Average Quartiles

Models (Std. Error)	*Postsecondary Outcomes Credit Hours: Attempted*				
	Full Sample	H.S. GPA: Q1 (1.085-2.720)	H.S. GPA: Q2 (2.722-3.200)	H.S. GPA: Q3 (3.204-3.701)	H.S. GPA: Q4 (3.710-5.000)
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Carroll Scholarship Amount ($100)	0.365***	0.430***	0.314***	0.363***	0.0916
	(0.0209)	(0.0339)	(0.0455)	(0.0386)	(0.151)
Other Aid Amount ($100)	0.221***	0.183***	0.109***	0.294***	0.321***
	(0.0266)	(0.0482)	(0.0390)	(0.0388)	(0.0627)
Pell Grant Recipient	-0.169	1.549**	-2.974***	-0.443	-3.268
	(0.504)	(0.670)	(0.992)	(1.048)	(2.168)
Pell Grant Amount ($100)	0.164***	0.139***	0.341***	0.107*	0.112
	(0.0235)	(0.0329)	(0.0366)	(0.0610)	(0.0930)
Dual Credit Enrollee	0.587*	0.872**	-2.305***	-2.339***	-1.397
	(0.301)	(0.404)	(0.720)	(0.852)	(1.435)
H.S. GPA	0.525**	0.937**	3.235	-1.157	-5.159***
	(0.206)	(0.444)	(1.987)	(1.588)	(1.767)
Male	0.983***	1.005***	1.519***	0.720	1.674
	(0.245)	(0.386)	(0.500)	(0.515)	(1.230)
White	0.901*	-0.433	0.237	4.026***	-3.220
	(0.546)	(0.869)	(0.964)	(1.346)	(2.267)
Constant	2.376**	2.029	-1.775	7.845	32.81***
	(1.101)	(1.853)	(5.614)	(5.729)	(9.413)
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Carroll)	227	107	56	50	14
N. Control (No Carroll)	520	213	135	128	44
Observations	747	320	191	178	58
R-squared	0.537	0.534	0.545	0.705	0.793

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for *Carroll Scholarship Amount*, Other Aid Amount, and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. Non-Dual Credit, Female, and Non-White are the omitted variable categories. The treatment and control groups consist of Meridian students exclusively. *Carroll Scholarship Amount* is a continuous treatment variable for the value of Carroll Scholarship funding that a student receives each semester (*Carroll Scholarship Amount*= “value”, If a student does not receive the Carroll Scholarship, *Carroll Scholarship Amount*= 0). Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards. The models measure the Average Treatment Effect (ATE) because each member of the treatment group is receiving Carroll Scholarship funding, not just information on postsecondary affordability.
*** p<0.01, ** p<0.05, * p<0.1.

Table 23.
Difference-in-Difference Models for Postsecondary Credit Hours Earned at Richland: Received Carroll Scholarship Funding Treatment Condition: separated by High School Grade Point Average Quartiles

	Postsecondary Outcomes				
	Credit Hours: Earned				
Models (Std. Error)	Full Sample	H.S. GPA: Q1 (1.085-2.720)	H.S. GPA: Q2 (2.722-3.200)	H.S. GPA: Q3 (3.204-3.701)	H.S. GPA: Q4 (3.710-5.000)
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Carroll Scholarship Recipient	4.376***	4.773***	3.987***	4.218***	0.392
	(0.397)	(0.589)	(0.808)	(0.904)	(1.543)
Other Aid Amount ($100)	0.197***	0.0987	0.111**	0.246***	0.285***
	(0.0277)	(0.0604)	(0.0485)	(0.0454)	(0.0793)
Pell Grant Recipient	-2.159***	-1.784**	-3.479***	-0.345	-2.621
	(0.614)	(0.874)	(1.104)	(1.666)	(2.313)
Pell Grant Amount ($100)	0.232***	0.2267***	0.347***	0.0645	0.0663
	(0.0297)	(0.0398)	(0.0477)	(0.101)	(0.116)
Dual Credit Enrollee	0.757**	1.286**	-2.030**	-3.012***	-0.901
	(0.359)	(0.499)	(0.878)	(0.928)	(1.559)
H.S.GPA	1.428***	1.977***	2.725	-1.327	-8.818***
	(0.237)	(0.483)	(2.080)	(1.974)	(2.049)
Male	0.283	0.140	1.002*	-0.140	0.768
	(0.287)	(0.434)	(0.588)	(0.639)	(1.295)
White	1.213**	1.022	-1.868	4.866**	-2.626
	(0.549)	(0.768)	(1.414)	(1.903)	(2.568)
Constant	-0.938	-2.515	1.005	8.246	47.14***
	(1.173)	(1.548)	(6.108)	(7.020)	(11.04)
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Carroll)	227	107	56	50	14
N. Control (No Carroll)	520	213	135	128	44
Observations	747	320	191	178	58
R-squared	0.435	0.414	0.447	0.519	0.758

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. Non-Dual Credit, Female, and Non-White are the omitted variable categories. The treatment and control groups consist of Meridian students exclusively. *Carroll Scholarship Recipient* treatment is a binary measure identifying whether a student actually received Carroll Scholarship funds (Yes, *Carroll Scholarship Recipient*= 1, If a student does not receive a Carroll Scholarship, *Carroll Scholarship Recipient*= 0). Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards. The models measure the Average Treatment Effect (ATE) because each member of the treatment group is receiving Carroll Scholarship funding, not just information on postsecondary affordability.
*** p<0.01, ** p<0.05, * p<0.1.

Table 24.

Difference-in-Difference Models for Postsecondary Credit Hours Earned at Richland: Amount of Carroll Scholarship Received Treatment Condition: separated by High School Grade Point Average Quartiles

Models (Std. Error)	Postsecondary Outcomes Credit Hours: Earned				
	Full Sample	H.S. GPA: Q1 (1.085-2.720)	H.S. GPA: Q2 (2.722-3.200)	H.S. GPA: Q3 (3.204-3.701)	H.S. GPA: Q4 (3.710-5.000)
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Carroll Scholarship Amount ($100)	0.417***	0.527***	0.375***	0.340***	0.167
	(0.0218)	(0.0329)	(0.0503)	(0.0425)	(0.219)
Other Aid Amount ($100)	0.241***	0.137**	0.109**	0.279***	0.285***
	(0.0286)	(0.0594)	(0.0433)	(0.0450)	(0.0694)
Pell Grant Recipient	-1.406**	-1.006	-2.669**	0.427	-2.509
	(0.590)	(0.772)	(1.141)	(1.532)	(2.304)
Pell Grant Amount ($100)	0.215***	0.280***	0.330***	0.0499	0.061
	(0.0283)	(0.0367)	(0.0458)	(0.0934)	(0.103)
Dual Credit Enrollee	0.520	0.628	-2.034**	-2.911***	-0.807
	(0.332)	(0.399)	(0.845)	(0.886)	(1.603)
H.S. GPA	1.316***	1.456***	2.720	0.147	-9.334***
	(0.212)	(0.361)	(1.961)	(1.837)	(1.924)
Male	0.466*	0.445	1.027*	0.276	0.712
	(0.256)	(0.348)	(0.568)	(0.598)	(1.316)
White	1.836***	1.166	-0.212	5.264***	-2.522
	(0.579)	(0.820)	(1.022)	(1.931)	(2.595)
Constant	-1.096	-1.077	-0.648	2.823	49.05***
	(1.144)	(1.347)	(5.755)	(6.539)	(10.28)
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Carroll)	227	107	56	50	14
N. Control (No Carroll)	520	213	135	128	44
Observations	747	320	191	178	58
R-squared	0.520	0.583	0.489	0.582	0.759

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for *Carroll Scholarship Amount*, Other Aid Amount, and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. Non-Dual Credit, Female, and Non-White are the omitted variable categories. The treatment and control groups consist of Meridian students exclusively. *Carroll Scholarship Amount* is a continuous treatment variable for the value of Carroll Scholarship funding that a student receives each semester (*Carroll Scholarship Amount*= "value", If a student does not receive the Carroll Scholarship, *Carroll Scholarship Amount*= 0). Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards. The models measure the Average Treatment Effect (ATE) because each member of the treatment group is receiving Carroll Scholarship funding, not just information on postsecondary affordability.

*** p<0.01, ** p<0.05, * p<0.1.

Table 25.

Difference-in-Difference Models for Postsecondary Credit Hours Attempted at Richland: Carroll Scholarship Information Treatment Condition: restricted to students with no unmet need based on registered credit hours: separated by High School Grade Point Average Quartiles

	Postsecondary Outcomes				
	Credit Hours: Attempted				
Model	Full Sample	H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
(Std. Error)	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
MERIDIAN x POST	1.384*	2.471	0.540	-0.990	3.028***
	(0.807)	(2.987)	(0.977)	(1.412)	(0.940)
Other Aid Amount ($100)	0.188***	0.165***	0.132***	0.232***	0.224***
	(0.0159)	(0.0408)	(0.0283)	(0.0312)	(0.028)
Pell Grant Recipient	-2.822***	-1.753	-3.685***	-2.357***	-2.132***
	(0.389)	(1.126)	(0.798)	(0.702)	(0.629)
Pell Grant Amount ($100)	0.302***	0.340***	0.377***	0.307***	0.192***
	(0.0129)	(0.0187)	(0.0225)	(0.0367)	(0.0288)
Constant	5.298***	4.115***	6.640***	4.850***	5.372***
	(0.551)	(1.075)	(0.996)	(1.285)	(1.104)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	242	67	69	64	33
N. Control (In-District)	3,222	767	593	725	987
Number of id	1,225	319	234	270	325
Observations	3,464	834	662	789	1,020
R-squared	0.613	0.638	0.678	0.588	0.671

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. The treatment and control groups consist of students who had no unmet need during the semester. Unmet need is calculated by multiplying the per credit hour tuition rate at Richland by the number of registered credit hours, and subtracting the value of non-Carroll Scholarship financial aid award. *Carroll Scholarship Recipients* are omitted from this sample. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards.
*** p<0.01, ** p<0.05, * p<0.1.

Table 26.

Difference-in-Difference Models for Postsecondary Credit Hours Earned at Richland: Carroll Scholarship Information Treatment Condition: restricted to students with no unmet need based on registered credit hours: separated by High School Grade Point Average Quartiles

Model (Std. Error)	*Postsecondary Outcomes Credit Hours: Earned*				
	Full Sample	H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
MERIDIAN x POST	2.485***	1.305	3.375***	1.127	3.001***
	(0.730)	(1.184)	(0.778)	(2.728)	(0.987)
Other Aid Amount ($100)	0.163***	0.118***	0.108***	0.218***	0.184***
	(0.0160)	(0.0384)	(0.0390)	(0.0328)	(0.0301)
Pell Grant Recipient	-2.410***	-2.586*	-2.832***	-2.580***	-1.645**
	(0.427)	(1.350)	(1.033)	(0.787)	(0.739)
Pell Grant Amount ($100)	0.251***	0.290***	0.259***	0.293***	0.167***
	(0.0150)	(0.0224)	(0.0290)	(0.0385)	(0.0340)
Constant	4.633***	3.578**	3.275***	3.881***	6.261***
	(0.640)	(1.451)	(0.996)	(1.394)	(1.301)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	242	67	69	64	33
N. Control (In-District)	3,222	767	593	725	987
Number of id	1,225	319	234	270	325
Observations	3,464	834	662	789	1,020
R-squared	0.390	0.355	0.386	0.427	0.520

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. The treatment and control groups consist of students who had no unmet need during the semester. Unmet need is calculated by multiplying the per credit hour tuition rate at Richland by the number of registered credit hours, and subtracting the value of non-Carroll Scholarship financial aid award. *Carroll Scholarship Recipients* are omitted from this sample. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards.

*** p<0.01, ** p<0.05, * p<0.1.

Table 27.

Difference-in-Difference Models for Postsecondary Credit Hours Attempted at Richland: Carroll Scholarship Funding Treatment Condition: restricted to students with no unmet need based on registered credit hours: separated by High School Grade Point Average Quartiles

Model (Std. Error)	*Postsecondary Outcomes Credit Hours: Attempted*				
	Full Sample	H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
MERIDIAN x POST	1.119	0.0539	2.062	1.061	-0.416
	(0.735)	(0.662)	(1.409)	(0.770)	(1.709)
Other Aid Amount ($100)	0.183***	0.158***	0.122***	0.233***	0.224***
	(0.0154)	(0.0393)	(0.0258)	(0.0307)	(0.029)
Pell Grant Recipient	-2.786***	-1.581	-3.529***	-2.417***	-1.949***
	(0.368)	(1.031)	(0.830)	(0.677)	(0.578)
Pell Grant Amount ($100)	0.300***	0.339***	0.374***	0.308***	0.177***
	(0.0131)	(0.0184)	(0.0235)	(0.0368)	(0.0274)
Constant	5.327***	4.316***	6.669***	2.051	5.323***
	(0.558)	(1.009)	(1.023)	(1.486)	(1.102)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	302	116	69	78	31
N. Control (In-District)	3,222	767	593	725	987
Number of id	1,252	335	236	276	326
Observations	3,524	883	662	803	1,018
R-squared	0.596	0.612	0.645	0.589	0.670

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. The treatment and control groups consist of students who had no unmet need during the semester. Unmet need is calculated by multiplying the per credit hour tuition rate at Richland by the number of registered credit hours, and subtracting the value of non-Carroll Scholarship financial aid award. Meridian student's, who did not require the Carroll Scholarship to cover any unmet need, after the start of the scholarship program, are omitted from this sample. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards.

*** p<0.01, ** p<0.05, * p<0.1.

Table 28.

Difference-in-Difference Models for Postsecondary Credit Hours Earned at Richland: Carroll Scholarship Funding Treatment Condition: restricted to students with no unmet need based on registered credit hours: separated by High School Grade Point Average Quartiles

Model (Std. Error)	*Postsecondary Outcomes Credit Hours: Earned*				
	Full Sample	H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
MERIDIAN x POST	2.663***	2.302**	3.918**	1.156	-0.0200
	(0.951)	(1.075)	(1.532)	(1.027)	(1.712)
Other Aid Amount ($100)	0.157***	0.107***	0.0946***	0.228***	0.185***
	(0.0157)	(0.0383)	(0.0337)	(0.0315)	(0.0313)
Pell Grant Recipient	-2.447***	-2.703**	-2.294**	-2.644***	-1.418**
	(0.407)	(1.226)	(1.068)	(0.762)	(0.693)
Pell Grant Amount ($100)	0.251***	0.295***	0.263***	0.297***	0.150***
	(0.0153)	(0.0224)	(0.0306)	(0.0388)	(0.0330)
Constant	4.902***	3.780***	3.264***	1.759	6.199***
	(0.663)	(1.235)	(1.082)	(1.605)	(1.314)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	302	116	69	78	31
N. Control (In-District)	3,222	767	593	725	987
Number of id	1,252	335	236	276	326
Observations	3,524	883	662	803	1,018
R-squared	0.380	0.342	0.370	0.439	0.516

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. The treatment and control groups consist of students who had no unmet need during the semester. Unmet need is calculated by multiplying the per credit hour tuition rate at Richland by the number of registered credit hours, and subtracting the value of non-Carroll Scholarship financial aid award. Meridian student's, who did not require the Carroll Scholarship to cover any unmet need, after the start of the scholarship program, are omitted from this sample. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards.
*** p<0.01, ** p<0.05, * p<0.1.

Table 29.

Difference-in-Difference Models for Postsecondary Credit Hours Attempted at Richland: Carroll Scholarship Information Treatment Condition: restricted to students who are Pell Grant Recipients and have no unmet need: separated by High School Grade Point Average Quartiles

	Postsecondary Outcomes Credit Hours: Attempted				
Model (Std. Error)	Full Sample	H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
MERIDIAN x POST	1.410*	9.648***	0.428	0.187	0.834
	(0.778)	(0.622)	(1.137)	(1.095)	(0.628)
Other Aid Amount ($100)	0.0883***	0.0597*	0.0774**	0.120***	0.123***
	(0.0138)	(0.0307)	(0.0334)	(0.0342)	(0.0284)
Pell Grant Amount ($100)	0.380***	0.385***	0.405***	0.404***	0.321***
	(0.0125)	(0.0172)	(0.0215)	(0.0388)	(0.0321)
Constant	1.897***	1.538***	2.402***	2.798***	1.674*
	(0.381)	(0.551)	(0.897)	(0.329)	(0.943)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	183	53	67	31	23
N. Control (In-District)	2,019	622	446	426	400
Number of id	781	251	171	161	138
Observations	2,202	675	513	457	423
R-squared	0.709	0.754	0.738	0.655	0.740

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. The treatment and control groups consist of students who had no unmet need during the semester and are awarded a Pell Grant. Unmet need is calculated by multiplying the per credit hour tuition rate at Richland by the number of registered credit hours, and subtracting the value of non-Carroll Scholarship financial aid award. Meridian students who received the Carroll Scholarship are omitted from this sample. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards.

*** p<0.01, ** p<0.05, * p<0.1.

Table 30.

Difference-in-Difference Models for Postsecondary Credit Hours Earned at Richland: Carroll Scholarship Information Treatment Condition: restricted to students who are Pell Grant Recipients and have no unmet need: separated by High School Grade Point Average Quartiles

	Postsecondary Outcomes *Credit Hours: Earned*				
Model (Std. Error)	Full Sample	H.S. GPA: Q1 (1.085-2.648)	H.S. GPA: Q2 (2.650-3.170)	H.S. GPA: Q3 (3.172-3.700)	H.S. GPA: Q4 (3.701-5.000)
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
MERIDIAN x POST	2.737***	4.794***	3.341***	3.788**	0.674
	(0.515)	(0.977)	(1.011)	(1.492)	(0.780)
Other Aid Amount ($100)	0.0706***	0.0386	0.0435	0.107***	0.0897***
	(0.0162)	(0.0359)	(0.0489)	(0.0399)	(0.0285)
Pell Grant Amount ($100)	0.327***	0.319***	0.287***	0.397***	0.325***
	(0.0149)	(0.0223)	(0.0299)	(0.0406)	(0.0350)
Constant	1.419**	-0.0985	3.377***	2.215**	0.620
	(0.559)	(1.102)	(1.240)	(1.035)	(1.214)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes
Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	183	53	67	31	23
N. Control (In-District)	2,019	622	446	426	400
Number of id	781	251	171	161	138
Observations	2,202	675	513	457	423
R-squared	0.419	0.396	0.435	0.423	0.569

Note. Robust standard errors in parentheses. Coefficients and Standard Errors for Other Aid Amount and Pell Grant Award are multiplied by 100 to signify the impact of $100 dollars in aid award. The treatment and control groups consist of students who had no unmet need during the semester and are awarded a Pell Grant. Unmet need is calculated by multiplying the per credit hour tuition rate at Richland by the number of registered credit hours, and subtracting the value of non-Carroll Scholarship financial aid award. Meridian students who received the Carroll Scholarship are omitted from this sample. Other Aid Amount excludes Carroll Scholarship awards and Pell Grant awards.

*** p<0.01, ** p<0.05, * p<0.1.

Table 31.

Difference-in-Difference Models for Students following a Postsecondary Associates Degree Path: Carroll Scholarship Eligibility Treatment Condition: separated by High School Grade Point Average Quartiles

Models (Std. Error)	Postsecondary Student Decisions Associates Degree Path					
	Full Sample		H.S. GPA: Q1 & Q2 (1.085-3.200)		H.S. GPA: Q3 & Q4 (3.204-5.000)	
	(1) OLS	(2) Logistic	(3) OLS	(4) Logistic	(5) OLS	(6) Logistic
MERIDIAN x POST	0.00118	0.751	0.0730	1.367	-0.0926**	2.25e-07***
	(0.0533)	(0.404)	(0.0870)	(1.072)	(0.0236)	(2.40e-07)
MERIDIAN	-0.0426	0.558	-0.111	0.338	0.0445***	1.288e+06***
	(0.0520)	(0.286)	(0.0833)	(0.242)	(0.00818)	(1.174e+06)
POST	0.167***	6.610***	0.120***	4.420***	0.0350***	2.315***
	(0.00144)	(0.299)	(0.00581)	(0.549)	(0.00173)	(0.138)
Dual Credit Enrollee	0.0328*	1.900***	0.0384**	2.027***	0.0135	1.636
	(0.0149)	(0.411)	(0.0115)	(0.514)	(0.0252)	(1.415)
Male	-0.0250**	0.632***	-0.0568**	0.337***	0.0131*	1.654***
	(0.00743)	(0.0699)	(0.0176)	(0.118)	(0.00513)	(0.302)
White	0.00417	1.072	-0.0223	0.622	0.0212	1.965
	(0.0119)	(0.243)	(0.0201)	(0.294)	(0.0270)	(1.067)
Constant	0.786***	3.545***	0.864***	11.34***	0.905***	5.582***
	(0.0101)	(0.714)	(0.0202)	(6.057)	(0.0175)	(1.683)
Non-Meridian High School Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Academic Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	125	125	82	82	39	39
N. Control (In-District)	1,250	1,250	548	548	612	612
Observations	1,375	1,375	630	630	651	651
R-squared (Pseudo)	0.032	0.059	0.050	0.097	0.015	0.057

Note. Standard errors clustered by Academic Year. *MERIDIAN* is a dummy variable. School ID Number 5625 is the omitted Non-Meridian High School dummy variable. The Year Fixed Effect is associated with the last semester a student enrolled at Richland Non-Dual Credit, Female, and Non-White are the omitted variable categories. Logistic models report Odds Ratio coefficient results. Logistic models report Pseudo R-squared. *Associates Degree Path* is a binary dependent variable. *Associates Degree Path*= 1 if a student has identified following a curriculum associated with an Associate's Degree; *Associates Degree Path*= 0 if a student has selected a non-Associates Degree curriculum. Students who have selected a transfer curriculum not associated with an Associate's degree have been omitted from this sample. The curricular path identified during a student's last semester is assumed to be the final decision at Richland. Models separated by *HS GPA* quartile 1 & 2 and *HS GPA* quartile 3 & 4 because Logistic regression is based off the dependent variables observations equal to one (*Associates Degree Path*= 1). Separating the sample by HS GPA quartiles creates small sample size problems for Meridian students with *Associates Degree Path*= 1. For this reason I combine the lower two and upper two *HS GPA* quartiles. The models measure the Intention to Treat (ITT) because each member of the treatment group is receiving information on postsecondary affordability, but is not necessarily receiving Carroll Scholarship funding.
*** p<0.01, ** p<0.05, * p<0.1.

Table 32.

Difference-in-Difference Models for Students following a Postsecondary Transferable Curricular Path: Carroll Scholarship Eligibility Treatment Condition: separated by High School Grade Point Average Quartiles

	Postsecondary Student Decisions *Transferable Degree Path*					
	Full Sample		H.S. GPA: Q1 & Q2 (1.085-3.200)		H.S. GPA: Q3 & Q4 (3.204-5.000)	
Models (Std. Error)	(1) OLS	(2) Logistic	(3) OLS	(4) Logistic	(5) OLS	(6) Logistic
MERIDIAN x POST	-0.00671	0.733	0.0615	1.638	-0.0723**	2.26e-07***
	(0.0152)	(0.159)	(0.0440)	(0.985)	(0.0202)	(1.93e-07)
MERIDIAN	-0.0209	0.642**	-0.0831*	0.344**	0.0329***	1.213e+06***
	(0.0146)	(0.133)	(0.0407)	(0.181)	(0.00576)	(850,312)
POST	0.0943***	4.674***	0.0665***	3.106***	0.0199***	2.063***
	(0.00118)	(0.169)	(0.00497)	(0.416)	(0.00205)	(0.144)
Dual Credit Enrollee	0.0258*	1.910***	0.0285***	1.947***	0.0127	1.781
	(0.0111)	(0.376)	(0.00651)	(0.433)	(0.0213)	(1.625)
Male	-0.0152**	0.694***	-0.0426**	0.352***	0.0119**	1.779***
	(0.00459)	(0.0688)	(0.0127)	(0.116)	(0.00391)	(0.304)
White	0.00619	1.152	-0.0141	0.690	0.0153	1.842
	(0.00820)	(0.243)	(0.0162)	(0.323)	(0.0212)	(1.068)
Constant	0.865***	5.795***	0.918***	18.50***	0.933***	8.210***
	(0.00709)	(1.090)	(0.0153)	(9.627)	(0.0133)	(2.169)
Non-Meridian High School Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Academic Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	176	176	115	115	51	51
N. Control (In-District)	1,646	1,646	722	722	783	783
Observations	1,822	1,822	837	837	834	834
R-squared (Pseudo)	0.018	0.044	0.031	0.074	0.011	0.054

Note. Standard errors clustered by Academic Year. *MERIDIAN* is a dummy variable. School ID Number 5625 is the omitted Non-Meridian High School dummy variable. The Year Fixed Effect is associated with the last semester a student enrolled at Richland. Non-Dual Credit, Female, and Non-White are the omitted variable categories. Logistic models report Odds Ratio coefficient results. Logistic models report Pseudo R-squared. *Transferable Degree Path* = 1 if a student has identified following a curriculum associated with an Associate's Degree or a transfer course outline; *Transferable Degree Path* = 0 if a student has selected a non-Associates Degree curriculum or a curriculum that does not transfer. *Transferable Degree Path* is an additive variable that contains *Associates Degree Path* and Richland's transfer curriculum that contains transferable courses but is not aligned with an Associate's Degree. The curricular path identified during a student's last semester is assumed to be the final decision at Richland. Models separated by *HS GPA* quartile 1 & 2 and *HS GPA* quartile 3 & 4 because Logistic regression is based off the dependent variables observations equal to one (*Transferable Degree Path*= 1). Separating the sample by HS GPA quartiles creates small sample size problems for Meridian students with *Transferable Degree Path*= 1. For this reason I combine the lower two and upper two *HS GPA* quartiles. The models measure the Intention to Treat (ITT) because each member of the treatment group is receiving information on postsecondary affordability, but is not necessarily receiving Carroll Scholarship funding.

*** p<0.01, ** p<0.05, * p<0.1.

Table 33.

Parents' College Asset Methods, Definitions, Number of Observations, Combined Strategy Identification, and Average Number of Different Methods Used by Households that Save

Variable	Survey Question: Have you or your spouse/partner done anything specific in order to have some money for your tenth grader's education after high school?	N	*Past Account Creation*	*Past Account Creation + Past Asset Reallocation*	*Past Account Creation + Past Asset Reallocation + Future Intention*	Average No. of Individual Methods Used When the Portfolio Includes:
Previously Established Individual Holding Methods:						
Savings	Started a savings account	4,201	X	X	X	4.58
Insurance	Bought an insurance policy	1,981	X	X	X	5.23
U.S. bonds	Bought U.S. savings bonds	2,061	X	X	X	5.06
Other Savings	Established another form of savings	1,672	X	X	X	5.21
Stock/Real Estate	Made investment in stocks/real estate	3,015	X	X	X	4.79
State program *	Participated in state-sponsored college savings program	676	X	X	X	4.82
College fund *	Set up a college investment fund	1,994	X	X	X	4.82
Previous Household Sacrifices and Decisions to Reallocate Assets:						
Remortgage	Remortgaged property/took out home-equity loan	533		X	X	6.17
Reduce Expense	Reduced other expenses in some way	2,407		X	X	5.29
Add Job	Started working another job/more hours	1,265		X	X	5.4
Identified Future Intentions to Accrue Savings:						
Plan to Reduce Expense	Planned to reduce other expenses in some way	3,070			X	5.06
Plan to Remortgage	Planned to remortgage property/take out home-equity	812			X	5.73
Avg. No. of Methods used within each Combined Strategy:			2.73	4.14	5.54	4.18

Note: * denotes that *State program* and *College Fund* are combined to represent college *529 savings*.

Table 34.

Population Means for the Pre- and Post-Match Sample, the Standardized Mean Difference, and the Test Results for the Null Hypothesis that the Standardized Mean Difference = 0: Past Account Creation

	Pre-Matching Means		Post-Matching Means		Mean	Null Hypothesis
Matching Estimators	Treatment	Control	Treatment	Control	Std. Diff.	p-value
catholic	0.1796	0.1170	0.1796	0.1705	0.0269	0.5561
father_college	0.7417	0.5327	0.7417	0.7144	0.0564	0.1314
female	0.5091	0.5315	0.5091	0.4834	0.0514	0.2073
freelunch	2.6076	3.3929	2.6076	2.6126	-0.0026	0.9445
guidance	3.6126	3.6362	3.6126	3.6987	-0.0342	0.3969
income_q1	0.0662	0.2588	0.0662	0.0687	-0.0062	0.8078
income_q2	0.2020	0.3598	0.2020	0.1978	0.0090	0.7993
income_q3	0.2334	0.2103	0.2334	0.2334	0.0000	1.0000
income_q4	0.2169	0.1076	0.2169	0.2136	0.0098	0.8431
income_q5	0.2815	0.0636	0.2815	0.2864	-0.0160	0.7867
male	0.4909	0.4685	0.4909	0.5166	-0.0514	0.2073
midwest	0.2724	0.2642	0.2724	0.2748	-0.0056	0.8912
mother_college	0.7632	0.5538	0.7632	0.7326	0.0638	0.0830
northeast	0.1614	0.1923	0.1614	0.1531	0.0214	0.5765
parent_expects	0.9975	0.9849	0.9975	0.9967	0.0076	0.7052
parentinfo	0.3675	0.1084	0.3675	0.3303	0.0197	0.5873
pretest	54.7624	50.8426	54.7624	54.9138	-0.0165	0.6758
private	0.1283	0.0733	0.1283	0.1275	0.0029	0.9515
public	0.6921	0.8097	0.6921	0.7020	-0.0241	0.5954
race_amind	0.0050	0.0077	0.0050	0.0116	-0.0794	0.0725
race_asian	0.0712	0.0745	0.0712	0.0911	-0.0761	0.0738
race_black	0.0728	0.1184	0.0728	0.0728	0.0000	1.0000
race_hispanic	0.0464	0.0904	0.0464	0.0447	0.0061	0.8453
race_hispanic_no	0.0306	0.0884	0.0306	0.0273	0.0127	0.6277
race_two	0.0406	0.0425	0.0406	0.0497	-0.0454	0.2811
race_white	0.7334	0.5780	0.7334	0.7028	0.0636	0.0944
rural	0.1796	0.2174	0.1796	0.1548	0.0613	0.1020
siblings_0	0.2177	0.1874	0.2177	0.2202	-0.0063	0.8827
siblings_1	0.4627	0.3646	0.4627	0.4545	0.0170	0.6832
siblings_2	0.2384	0.2682	0.2384	0.2376	0.0019	0.9619
siblings_3	0.0563	0.1096	0.0563	0.0671	-0.0367	0.2718
siblings_4	0.0166	0.0451	0.0166	0.0157	0.0044	0.8718
siblings_4plus	0.0083	0.0251	0.0083	0.0050	0.0232	0.3159
south	0.3733	0.3518	0.3733	0.3560	0.0363	0.3750
student_expects	0.9255	0.8559	0.9255	0.9371	-0.0350	0.2604
suburban	0.4975	0.4748	0.4975	0.5174	-0.0398	0.3289
urban	0.3228	0.3078	0.3228	0.3278	-0.0107	0.7945
west	0.1929	0.1917	0.1929	0.2161	-0.0588	0.1580
pscore	0.3909	0.2096	0.3909	0.3908	0.0007	0.9886

Note. The p-value is reported for the null hypothesis that the post-matching mean standardized differences for each variable for the treatment population is equal to post-matching mean standardized differences for the control group.

Table 35.

Population Means for the Pre- and Post-Match Sample, the Standardized Mean Difference, and the Test Results for the Null Hypothesis that the Standardized Mean Difference = 0: Past Account Creation + Past Asset Reallocation

	Pre-Matching Means		Post-Matching Means		Mean	Null Hypothesis
Matching Estimators	Treatment	Control	Treatment	Control	Std. Diff.	p-value
catholic	0.2122	0.1138	0.2122	0.2280	-0.0480	0.5708
father_college	0.7449	0.5312	0.7449	0.7336	0.0229	0.7024
female	0.5666	0.5306	0.5666	0.5824	-0.0317	0.6348
freelunch	2.7223	3.4071	2.7223	2.7223	0.0000	1.0000
guidance	3.6591	3.6347	3.6591	3.5327	0.0500	0.4570
income_q1	0.0858	0.2592	0.0858	0.1016	-0.0373	0.4202
income_q2	0.2212	0.3589	0.2212	0.1986	0.0477	0.4100
income_q3	0.2506	0.2138	0.2506	0.2528	-0.0055	0.9384
income_q4	0.2077	0.1066	0.2077	0.2144	-0.0211	0.8052
income_q5	0.2348	0.0615	0.2348	0.2325	0.0085	0.9368
male	0.4334	0.4694	0.4334	0.4176	0.0317	0.6348
midwest	0.2980	0.2661	0.2980	0.3273	-0.0661	0.3467
mother_college	0.7630	0.5536	0.7630	0.7698	-0.0138	0.8120
northeast	0.1874	0.1927	0.1874	0.2032	-0.0401	0.5535
parent_expects	0.9977	0.9618	0.9977	0.9977	0.0000	1.0000
parentinfo	0.4424	0.0980	0.4424	0.3883	0.0284	0.5783
pretest	54.6324	50.6380	54.6324	54.1486	0.0519	0.4349
private	0.0993	0.0717	0.0993	0.1016	-0.0086	0.9111
public	0.6885	0.8145	0.6885	0.6704	0.0454	0.5652
race_amind	0.0045	0.0083	0.0045	0.0000	0.0510	0.1572
race_asian	0.0677	0.0734	0.0677	0.0587	0.0348	0.5813
race_black	0.1016	0.1177	0.1016	0.1242	-0.0705	0.2889
race_hispanic	0.0429	0.0906	0.0429	0.0497	-0.0243	0.6319
race_hispanic_no	0.0271	0.0897	0.0271	0.0316	-0.0164	0.6909
race_two	0.0451	0.0446	0.0451	0.0497	-0.0219	0.7522
race_white	0.7111	0.5757	0.7111	0.6862	0.0507	0.4212
rural	0.1941	0.2215	0.1941	0.1874	0.0164	0.7978
siblings_0	0.1964	0.1900	0.1964	0.1941	0.0057	0.9326
siblings_1	0.4041	0.3603	0.4041	0.3679	0.0750	0.2700
siblings_2	0.2393	0.2647	0.2393	0.2325	0.0154	0.8126
siblings_3	0.1084	0.1105	0.1084	0.1512	-0.1369	0.0576
siblings_4	0.0339	0.0465	0.0339	0.0406	-0.0326	0.5951
siblings_4plus	0.0181	0.0280	0.0181	0.0135	0.0279	0.5905
south	0.3205	0.3470	0.3205	0.2844	0.0760	0.2424
student_expects	0.9074	0.8416	0.9074	0.9120	-0.0126	0.8149
suburban	0.4831	0.4722	0.4831	0.4740	0.0181	0.7882
urban	0.3228	0.3063	0.3228	0.3386	-0.0342	0.6176
west	0.1941	0.1941	0.1941	0.1851	0.0228	0.7321
pscore	0.1878	0.0993	0.1878	0.1877	0.0013	0.9880

Note. The p-value is reported for the null hypothesis that the post-matching mean standardized differences for each variable from the treatment population is equal to post-matching mean standardized differences for the control group.

Table 36.

Population Means for the Pre- and Post-Match Sample, the Standardized Mean Difference, and the Test Results for the Null Hypothesis that the Standardized Mean Difference = 0: Past Account Creation + Past Asset Reallocation + Future Intention

	Pre-Matching Means		Post-Matching Means		Mean	Null Hypothesis
Matching Estimators	Treatment	Control	Treatment	Control	Std. Diff.	p-value
catholic	0.1907	0.1065	0.1907	0.2175	-0.0796	0.0543
father_college	0.7243	0.5073	0.7243	0.7320	-0.0159	0.6146
female	0.5033	0.5198	0.5033	0.4997	0.0071	0.8362
freelunch	2.8467	3.4572	2.8467	2.7837	0.0331	0.3223
guidance	3.8645	3.6311	3.8645	3.7195	0.0565	0.1054
income_q1	0.1123	0.2653	0.1123	0.1188	-0.0160	0.5533
income_q2	0.2668	0.3727	0.2668	0.2650	0.0038	0.9069
income_q3	0.2608	0.2060	0.2608	0.2377	0.0558	0.1203
income_q4	0.1884	0.0988	0.1884	0.1990	-0.0325	0.4326
income_q5	0.1717	0.0572	0.1717	0.1794	-0.0272	0.5560
male	0.4967	0.4802	0.4967	0.5003	-0.0071	0.8362
midwest	0.2721	0.2624	0.2721	0.2888	-0.0377	0.2828
mother_college	0.7398	0.5313	0.7398	0.7398	0.0000	1.0000
northeast	0.1836	0.1889	0.1836	0.1860	-0.0061	0.8591
parent_expects	0.9964	0.8872	0.9964	0.9970	-0.0022	0.7627
parentinfo	0.3856	0.0743	0.3856	0.3928	-0.0038	0.8910
pretest	53.8002	50.0308	53.8002	53.9194	-0.0127	0.7052
private	0.0927	0.0677	0.0927	0.0933	-0.0023	0.9527
public	0.7166	0.8259	0.7166	0.6892	0.0680	0.0828
race_amind	0.0083	0.0100	0.0083	0.0107	-0.0245	0.4775
race_asian	0.1028	0.0692	0.1028	0.0915	0.0418	0.2690
race_black	0.1313	0.1236	0.1313	0.1378	-0.0197	0.5786
race_hispanic	0.0523	0.0911	0.0523	0.0594	-0.0264	0.3679
race_hispanic_no	0.0511	0.0886	0.0511	0.0535	-0.0089	0.7569
race_two	0.0368	0.0439	0.0368	0.0434	-0.0327	0.3340
race_white	0.6174	0.5737	0.6174	0.6037	0.0278	0.4164
rural	0.1806	0.2236	0.1806	0.1848	-0.0102	0.7550
siblings_0	0.2109	0.1945	0.2109	0.1961	0.0372	0.2846
siblings_1	0.4070	0.3610	0.4070	0.4135	-0.0135	0.7000
siblings_2	0.2620	0.2645	0.2620	0.2585	0.0081	0.8137
siblings_3	0.0778	0.1072	0.0778	0.0802	-0.0080	0.7984
siblings_4	0.0255	0.0442	0.0255	0.0261	-0.0031	0.9135
siblings_4plus	0.0166	0.0286	0.0166	0.0255	-0.0571	0.0720
south	0.3714	0.3589	0.3714	0.3613	0.0210	0.5432
student_expects	0.9067	0.8162	0.9067	0.8978	0.0247	0.3841
suburban	0.4843	0.4733	0.4843	0.4813	0.0059	0.8631
urban	0.3351	0.3030	0.3351	0.3339	0.0026	0.9418
west	0.1729	0.1897	0.1729	0.1640	0.0230	0.4898
pscore	0.3985	0.2586	0.3985	0.3984	0.0005	0.9882

Note. The p-value is reported for the null hypothesis that the post-matching mean standardized differences for each variable from the treatment population is equal to post-matching mean standardized differences for the control group.

Table 37.

Statistics on Parents' College Asset participation by Student's Gender and Race and Ethnicity

Category		Male	Female	White	African-American	Hispanic
		Student Characteristics				
Sample Population:						
Parents' College Assets	n.	2,734	2,938	3,731	582	538
	%	24.8%	26.6%	33.8%	5.3%	4.9%
Non-Intent (No Savings)	n.	2,566	2,801	2,968	691	1,003
	%	23.2%	25.4%	26.9%	6.3%	9.1%
Sample Total	n.	5,300	5,739	6,699	1,273	1,541
	%	48.0%	52.0%	60.7%	11.5%	14.0%
Non-Response (omitted)	n.	1,137	1,208	1,011	467	311
Statistics on Parents' College Asset by Combined Treatment Strategy:						
Past Account Creation	n.	859	883	1,283	120	140
	%	31.4%	30.1%	34.4%	20.6%	26.0%
Past Account Creation + Past Asset Reallocation	n.	266	334	423	58	44
	%	9.7%	11.4%	11.3%	10.0%	8.2%
Past Account Creation + Past Asset Reallocation + Future Intention	n.	1,120	1,167	1,352	303	240
	%	41.0%	39.7%	36.2%	52.1%	44.6%
Statistics on Parents' College Asset by Individual Saving Methods:						
Savings	n.	2,036	2,165	2,735	471	386
	%	74.5%	73.7%	73.3%	80.9%	71.7%
Insurance	n.	943	1,038	1,226	278	177
	%	34.5%	35.3%	32.9%	47.8%	32.9%
U.S. Bonds	n.	1,027	1,034	1,507	185	118
	%	37.6%	35.2%	40.4%	31.8%	21.9%
Other Savings	n.	826	846	1,043	180	192
	%	30.2%	28.8%	28.0%	30.9%	35.7%
Stock/Real Estate	n.	1,474	1,541	2,178	228	228
	%	53.9%	52.5%	58.4%	39.2%	42.4%
529 plans	n.	1,151	1,186	1,624	215	164
	%	42.1%	40.4%	43.5%	36.9%	30.5%
Avg. No. of Savings Methods Used by Student Characteristic:		4.21	4.17	4.14	4.42	4.01

Table 38.
Statistics on Parents' College Asset participation by Household Income

Category		*Reported Household Income* Income Q1 ($0-25,000)	Income Q2 ($25,001-50,000)	Income Q3 ($50,001-75,000)	Income Q4 ($75,001-100,000)
Sample Population:					
Parents' College Assets	n.	563	1,320	1,289	1,056
	%	5.1%	12.0%	11.7%	9.6%
Non-Intent (No Savings)	n.	1,573	1,911	1,033	511
	%	14.2%	17.3%	9.4%	4.6%
Sample Total	n.	2,136	3,231	2,322	1,567
	%	19.3%	29.3%	21.0%	14.2%
Non-Response (omitted)	n.	739	963	589	362
Statistics on Parents' College Asset by Combined Treatment Strategy:					
Past Account Creation	n.	117	331	347	318
	%	20.8%	25.1%	26.9%	30.1%
Past Account Creation + Past Asset Reallocation	n.	58	128	144	112
	%	10.3%	9.7%	11.2%	10.6%
Past Account Creation + Past Asset Reallocation + Future Intention	n.	256	615	553	422
	%	45.5%	46.6%	42.9%	40.0%
Statistics on Parents' College Asset by Individual Saving Methods:					
Savings	n.	399	962	951	807
	%	70.9%	72.9%	73.8%	76.4%
Insurance	n.	179	493	429	405
	%	31.8%	37.3%	33.3%	38.4%
U.S. Bonds	n.	105	410	520	477
	%	18.7%	31.1%	40.3%	45.2%
Other Savings	n.	169	385	381	292
	%	30.0%	29.2%	29.6%	27.7%
Stock/Real Estate	n.	124	501	661	660
	%	22.0%	38.0%	51.3%	62.5%
529 plans	n.	137	404	488	474
	%	24.3%	30.6%	37.9%	44.9%
Avg. No. of Savings Methods Used by Household Income:		3.66	4.03	4.25	4.44

Table 39.

Statistics on Parents' College Asset participation by Student's Graduating High School GPA

Category		*Student Characteristic* High School Graduating GPA 0.00 - 1.00	1.01 - 1.50	1.51 - 2.00	2.01 - 2.50	2.51 - 3.00	3.01 - 3.50	3.51 - 4.00
Sample Population:								
Parents' College Assets	n.	28	114	362	791	1,179	1,421	1,398
	%	22.8%	33.2%	35.4%	42.9%	50.8%	58.7%	64.3%
Non-Intent (No Savings)	n.	95	229	662	1,054	1,143	1,001	776
	%	77.2%	66.8%	64.7%	57.1%	49.2%	41.3%	35.7%
Sample Total	n.	123	343	1,024	1,845	2,322	2,422	2,174
	%	1.2%	3.4%	10.0%	18.0%	22.7%	23.6%	21.2%
Non-Response (omitted)	n.	90	211	396	556	550	513	337
Statistics on Parents' College Asset by Combined Treatment Strategy:								
Past Account Creation	n.	6	21	100	221	374	460	442
	%	4.9%	6.1%	9.7%	12.0%	16.1%	19.0%	20.3%
Past Account Creation + Past Asset Reallocation	n.	2	8	32	90	97	153	166
	%	1.6%	2.3%	3.1%	4.9%	4.2%	6.3%	7.6%
Past Account Creation + Past Asset Reallocation + Future Intention	n.	14	66	172	341	489	547	528
	%	11.4%	19.2%	16.8%	18.5%	21.1%	22.6%	24.3%
Statistics on Parents' College Asset by Individual Saving Methods:								
Savings	n.	20	91	264	575	867	1051	1042
	%	16.3%	26.5%	25.8%	31.2%	37.3%	43.4%	47.9%
Insurance	n.	14	45	141	282	430	469	461
	%	11.4%	13.1%	13.8%	15.3%	18.5%	19.4%	21.2%
U.S. Bonds	n.	7	34	105	290	428	530	541
	%	5.7%	9.9%	10.3%	15.7%	18.4%	21.9%	24.9%
Other Savings	n.	11	46	110	223	351	432	385
	%	8.9%	13.4%	10.7%	12.1%	15.1%	17.8%	17.7%
Stock/Real Estate	n.	13	42	159	364	611	808	830
	%	10.6%	12.2%	15.5%	19.7%	26.3%	33.4%	38.2%
529 plans	n.	12	46	120	279	453	631	639
	%	9.8%	13.4%	11.7%	15.1%	19.5%	26.1%	29.4%
Avg. No. of Savings Methods Used by Student Characteristic:		4.56	4.54	4.20	4.12	4.20	4.25	4.29

Table 40.

Statistics on Parents' College Asset participation by Whether Parents and Students Discussed College, Parent's Postsecondary Expectations for their Student, Student's Own Postsecondary Expectations, Observed Student Enrolled, and Institution Type of Enrollment

Category		*Enrollment and Institution Type*						*Parent and Student Discussed college*		*Parent Expectations*		*Student Expectations*		
		Enrolled	2-yr	4-yr	Public, 4-yr	Private, 4-yr	Did not Enroll	Yes	No	≤ 4-yr	> 4-yr	Unsure	≤ 4-yr	> 4-yr
Sample Population:														
Parents' College Assets	n.	4,939	1,386	3,447	2,175	1,205	729	3,507	1,970	3,339	2,275	496	2,364	2,738
	%	44.7%	12.6%	31.2%	19.7%	10.9%	6.6%	31.8%	17.8%	30.2%	20.6%	4.5%	21.4%	24.8%
Non-Intent (No Savings)	n.	3,608	1,501	1,954	1,283	611	1,763	2,450	2,607	3,199	1,363	1,022	2,503	1,754
	%	32.7%	13.6%	17.7%	11.6%	5.5%	16.0%	22.2%	23.6%	29.0%	12.3%	9.3%	22.7%	15.9%
Sample Total	n.	8,547	2,887	5,404	3,458	1,816	2,492	5,957	4,577	6,538	3,638	1,518	4,867	4,537
	%	77.4%	26.2%	49.0%	31.3%	16.5%	22.6%	54.0%	41.5%	59.2%	33.0%	13.8%	44.1%	41.1%
Non-Response (omitted)	n.	1,987	804	1,085	720	319	1,013	1,039	1,028	66	45	449	1,086	736
Statistics on Parents' College Assets by Combined Treatment Strategies:														
Past Account Creation	n.	1,545	401	1,119	694	401	197	1,119	572	1,080	647	137	745	853
	%	31.3%	28.7%	32.4%	31.9%	33.3%	26.9%	18.8%	12.5%	32.3%	28.4%	27.6%	31.5%	31.2%
Past Account Creation +	n.	516	145	359	214	138	84	372	209	362	232	50	257	290
Past Asset Reallocation	%	10.4%	10.4%	10.4%	9.8%	11.5%	11.5%	6.2%	4.6%	10.8%	10.2%	10.1%	10.9%	10.6%
Past Account Creation + Past Asset Reallocation +	n.	1,971	598	1,338	850	460	316	1,405	811	1,259	1,006	202	953	1,118
Future Intention	%	39.9%	42.8%	38.8%	39.0%	38.2%	43.1%	23.6%	17.7%	37.7%	44.2%	40.7%	40.3%	40.8%
Statistics on Parents' College Assets by Individual Saving Methods:														
Savings	n.	3,641	1,020	2,556	1,622	886	560	2,652	1,414	2,442	1,724	374	1,747	2,053
	%	73.7%	73.1%	74.1%	74.5%	73.5%	76.4%	44.5%	30.9%	73.1%	75.8%	75.4%	73.9%	75.0%
Insurance	n.	1,705	500	1,176	726	422	276	1,214	692	1,124	843	177	814	972
	%	34.5%	35.8%	34.1%	33.3%	35.0%	37.7%	20.4%	15.1%	33.7%	37.1%	35.7%	34.4%	35.5%
U.S. Bonds	n.	1,852	496	1,328	842	458	209	1,314	686	1,208	839	168	848	1,038
	%	37.5%	35.5%	38.5%	38.7%	38.0%	28.5%	22.1%	15.0%	36.2%	36.9%	33.9%	35.9%	37.9%
Other Savings	n.	2,732	658	2,033	1,239	764	283	1,405	811	1,706	1,283	214	1,208	1,581
	%	55.3%	47.1%	58.9%	56.9%	63.4%	38.6%	23.6%	17.7%	51.1%	56.4%	43.1%	51.1%	57.7%
Stock/Real Estate	n.	1,444	418	1,002	633	904	753	1,962	966	904	753	151	698	815
	%	29.2%	29.9%	29.0%	29.1%	27.1%	33.1%	32.9%	21.1%	27.1%	33.1%	30.4%	29.5%	29.8%
529 plans	n.	2,123	488	1,606	985	595	214	1,549	721	1,281	1,041	165	924	1,239
	%	43.0%	35.0%	46.6%	45.2%	49.4%	29.2%	26.0%	15.8%	38.4%	45.8%	33.3%	39.1%	45.3%
Avg. No. of Savings Methods Used by Category:		4.22	4.13	4.27	4.23	4.34	3.96	4.14	4.30	4.01	4.45	4.09	4.11	4.27

Table 41.

Statistics on the Amount of Savings Accumulated by 10th grade, by Parents' College Asset Combined Strategies and Individual Holding Methods

		Amount Saved by Student's 10th grade year							
		None	< $2,000	$2,001 - $5,000	$5,001 - $10,000	$10,001 - $20,000	$20,001 - $30,000	$30,001 - $50,000	> $50,000
Sataistics on Amount Saved by Combined Treatment Strategy:									
Past Account Creation	n.	233	124	186	233	273	192	194	264
	%	3.9%	19.6%	21.7%	24.2%	31.3%	40.2%	47.2%	55.8%
Past Account Creation + Past Asset Reallocation	n.	85	61	94	93	93	53	42	59
	%	1.4%	9.6%	11.0%	9.6%	10.7%	11.1%	10.2%	12.5%
Past Account Creation + Past Asset Reallocation + Future Intention	n.	293	317	417	448	350	167	115	108
	%	4.9%	50.0%	48.7%	46.4%	40.2%	34.9%	28.0%	22.8%
Statistics on Amount Saved by Individual Saving Methods:									
Savings	n.	521	456	655	752	676	371	296	343
	%	8.7%	71.9%	76.4%	77.9%	77.6%	77.6%	72.0%	72.5%
Insurance	n.	244	201	301	335	334	178	151	175
	%	4.1%	31.7%	35.1%	34.7%	38.4%	37.2%	36.7%	37.0%
U.S. Bonds	n.	230	163	315	417	371	192	153	171
	%	3.9%	25.7%	36.8%	43.2%	42.6%	40.2%	37.2%	36.2%
Other Savings	n.	360	168	310	509	539	347	310	394
	%	6.0%	26.5%	36.2%	52.8%	61.9%	72.6%	75.4%	83.3%
Stock/Real Estate	n.	236	144	223	274	265	140	141	195
	%	4.0%	22.7%	26.0%	28.4%	30.4%	29.3%	34.3%	41.2%
529 plans	n.	253	126	264	391	431	254	250	311
	%	4.2%	19.9%	30.8%	40.5%	49.5%	53.1%	60.8%	65.8%
Avg. No. of Savings Methods Used by Amount Saved:		3.91	3.89	4.13	4.41	4.51	4.43	4.28	4.35

Table 42.

Correlation between Households Using Individual Parents' College Asset Options and Number of Families Using Each Combination

Individual Parents' College Asset Options	*Savings*	*Insurance*	*U.S. bonds*	*Stock/Real Estate*	*College fund*	*Other Savings*	*State program*	*Remortgage*	*Add Job*	*Reduce Expense*	*Plan To Reduce Expense*	*Plan To Remortgage*
Savings		1,619	1,654	2,292	1,499	1,273	502	401	954	1,846	2,341	595
Insurance	0.446		835	1,141	758	627	242	210	476	937	1,166	332
U.S. bonds	0.437	0.296		1,230	820	617	275	211	413	856	1,126	302
Stock/Real Estate	0.505	0.334	0.364		1,304	949	328	314	585	1,219	1,516	458
College fund	0.384	0.267	0.288	0.421		538	332	174	346	721	930	256
Other Savings	0.355	0.230	0.211	0.294	0.176		244	194	452	838	1,036	245
State program	0.215	0.129	0.157	0.133	0.214	0.167		73	154	284	378	99
Remortgage	0.188	0.137	0.131	0.169	0.088	0.148	0.076		192	347	403	214
Add Job	0.296	0.201	0.143	0.167	0.095	0.227	0.102	0.186		804	912	255
Reduce Expense	0.452	0.314	0.243	0.290	0.176	0.308	0.144	0.245	0.385		1,957	467
Plan To Reduce Exp.	0.522	0.348	0.308	0.348	0.215	0.340	0.173	0.249	0.377	0.650		601
Plan To Remortgage	0.226	0.178	0.145	0.195	0.110	0.135	0.081	0.306	0.183	0.254	0.303	
Percentage of Sample Population Using Each Individual Method (%):	39.1	18.6	19.3	28.2	18.7	15.8	6.3	4.9	11.5	22.0	28.1	7.5
Percentage of Households with Parents' College Assets Using Each Individual Method (%):	78.0	37.5	38.9	56.8	37.5	31.9	12.8	9.8	23.1	49.7	56.4	15.2

Note. Calculations below the diagonal line signify the correlation coefficient for the households that use the two individual savings alternatives. The number above the diagonal line is the number of households in the data sample that include both individual savings decisions in their savings portfolio.

Table 43a.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation: Binary Treatment Variable: any Postsecondary Institution Type

	Naïve, Unweighted		Matched	Post- Match, Weighted Regressions					
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Std. Error)	OLS	Logistic		OLS	Logistic	OLS	Logistic	OLS	Logistic
Models using Combined Strategy variable:									
Past Account Creation	0.202***	3.448***	0.0430***	0.0430***	1.501***	0.0397***	1.594***	0.0275	1.379
	(0.0107)	(0.292)	(0.0162)	(0.0133)	(0.188)	(0.0127)	(0.220)	(0.0289)	(0.440)
Sample Size:									
N. Treatment	1,485	1,485	1,208	1,208	1,208	1,208	1,208	1,125	1,125
N. Non-Intent (control)	5,107	5,107	3,505	3,505	3,505	3,505	3,505	3,250	3,250
Model Observations	6,592	6,592	4,713	2,416	2,416	2,416	2,416	2,250	2,250
(Pseudo) R-Squared	0.035	0.034	n.a.	0.085	0.118	0.189	0.232	0.248	0.303
Models conditioned on:									
pscores	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
covariates	No	No	No	No	No	Yes	Yes	Yes	Yes
Amount Saved & GPA	No	No	No	No	No	No	No	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 43b.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation: Binary Individual Savings Components Nested in Treatment Strategy, any Postsecondary Institution Type

Models	Naïve, Unweighted		Matched	Post- Match, Weighted Regressions					
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	Logistic		OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	0.0803***	1.639***	n.a.	0.00888	1.120	0.0229	1.268	0.0122	1.149
	(0.0171)	(0.208)	n.a.	(0.0182)	(0.180)	(0.0172)	(0.230)	(0.0189)	(0.276)
Insurance	-0.0118	0.866	n.a.	-0.00150	1.022	0.0139	1.219	0.0126	1.144
	(0.0193)	(0.147)	n.a.	(0.0194)	(0.208)	(0.0182)	(0.266)	(0.0189)	(0.285)
U.S. Bonds	0.0459***	1.466**	n.a.	0.0245	1.326	0.0157	1.264	0.0158	1.349
	(0.0173)	(0.247)	n.a.	(0.0180)	(0.279)	(0.0174)	(0.290)	(0.0178)	(0.360)
Stock/Real Estate	0.0777***	1.832***	n.a.	0.0187	1.225	-0.000489	1.054	-0.00999	0.893
	(0.0173)	(0.272)	n.a.	(0.0177)	(0.230)	(0.0168)	(0.214)	(0.0188)	(0.226)
Other Savings	0.0235	1.128	n.a.	-0.0339	0.714	-0.0345*	0.695	-0.0432**	0.531**
	(0.0209)	(0.205)	n.a.	(0.0219)	(0.147)	(0.0209)	(0.161)	(0.0211)	(0.136)
529 plan	0.120***	2.640***	n.a.	0.0400**	1.609**	0.0298**	1.611**	0.0259	1.707**
	(0.0151)	(0.395)	n.a.	(0.0156)	(0.308)	(0.0150)	(0.335)	(0.0169)	(0.432)
Sample Size:									
N. Savings	1,045	1,045	853	853	853	853	853	789	789
N. Insurance	435	435	358	358	358	358	358	327	327
N. U.S. Bonds	531	531	421	421	421	421	421	392	392
N. Stock/Real Estate	798	798	661	661	661	661	661	612	612
N. Other Savings	325	325	263	263	263	263	263	250	250
N. 529 plan	723	723	596	596	596	596	596	556	556
Model Observations	6,592	6,592	4,713	2,416	2,416	2,416	2,416	2,250	2,250
(Pseudo) R-Squared	0.034	0.037	n.a.	0.086	0.123	0.191	0.236	0.251	0.310
Models conditioned on:									
pscores	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
covariates	No	No	No	No	No	Yes	Yes	Yes	Yes
Amount Saved & GPA	No	No	No	No	No	No	No	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 44a.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation: Binary Treatment Variable: by Gender and Race and Ethnicity: any Postsecondary Institution Type

	Post-Match, Weighted Regressions									
	Student's Gender				*Student's Race and Ethnicity*					
Models	Male		Female		White		African-American		Hispanic	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Models using Combined Strategy variable:										
Past Account Creation	0.0361	1.495	0.0227	1.399	0.0248	1.569	0.155	3.003	-0.142	0.489
	(0.0470)	(0.544)	(0.0367)	(0.714)	(0.0337)	(0.613)	(0.106)	(2.381)	(0.154)	(0.449)
Sample Size:										
N. Treatment	555	555	570	510	824	824	81	75	87	56
N. Non-Intent (control)	591	591	534	534	496	496	59	59	59	50
Model Observations	1,146	1,146	1,104	1,044	1614	1614	162	156	173	133
R-Squared (Pseudo)	0.192	0.224	0.203	0.263	0.198	0.256	0.086	0.177	0.310	0.239
Models conditioned on:										
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 44b.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation: Binary Individual Savings Components Nested in Treatment Strategy: by Gender and Race and Ethnicity: any Postsecondary Institution Type

	Post-Match, Weighted Regressions									
	Student's Gender				*Student's Race and Ethnicity*					
Models	Male		Female		White		African-American		Hispanic	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	0.00321	1.150	0.0158	1.431	-0.000262	1.048	-0.0305	0.941	-0.0172	0.882
	(0.0320)	(0.345)	(0.0229)	(0.481)	(0.0219)	(0.301)	(0.109)	(0.683)	(0.0871)	(0.744)
Insurance	0.0214	1.246	-0.0129	0.720	0.00379	1.112	0.00268	0.944	0.0214	0.656
	(0.0310)	(0.430)	(0.0248)	(0.252)	(0.0221)	(0.356)	(0.0959)	(0.662)	(0.0654)	(0.555)
U.S. Bonds	0.0229	1.283	0.0227	1.481	0.0329*	1.600	0.0454	1.009	-0.00373	1.443
	(0.0281)	(0.410)	(0.0225)	(0.606)	(0.0197)	(0.491)	(0.0915)	(0.718)	(0.105)	(1.913)
Stock/Real Estate	0.0293	1.215	-0.0293	0.767	-0.0120	0.856	0.0765	1.510	0.0314	1.514
	(0.0284)	(0.378)	(0.0257)	(0.268)	(0.0208)	(0.235)	(0.108)	(1.281)	(0.0939)	(1.922)
Other Savings	-0.0381	0.677	-0.0529*	0.480**	-0.0367*	0.598*	-0.0141	0.610	-0.0377	0.586
	(0.0334)	(0.234)	(0.0287)	(0.174)	(0.0221)	(0.170)	(0.136)	(0.532)	(0.0954)	(0.673)
529 plan	0.0248	1.405	0.0257	1.780	0.0527***	2.362***	0.0815	2.539	-0.0477	0.677
	(0.0271)	(0.422)	(0.0207)	(0.684)	(0.0184)	(0.724)	(0.0885)	(1.966)	(0.0749)	(0.482)
Sample Size:										
N. Savings	390	390	399	359	568	568	62	56	59	38
N. Insurance	145	145	182	163	226	226	36	33	24	11
N. U.S. Bonds	190	190	202	176	312	312	25	23	18	13
N. Stock/Real Estate	295	295	317	268	481	481	30	26	39	19
N. Other Savings	112	112	138	121	201	201	11	10	18	10
N. 529 plan	286	286	270	230	427	427	33	30	40	24
Model Observations	1,146	1,146	1,104	1,044	1,614	1,614	162	156	173	133
R-Squared (Pseudo)	0.195	0.229	0.208	0.276	0.194	0.268	0.048	0.045	0.307	0.239
Models conditioned on:										
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 45a.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation: Binary Treatment Variable: by Household Income: any Postsecondary Institution Type

	Post-Match, Weighted Regressions							
	Reported Household Income							
Models	Income Q1 ($0-25,000)		Income Q2 ($25,001-50,000)		Income Q3 ($50,001-75,000)		Income Q4 ($75,001-100,000)	
(Std. Error)	(1) OLS	(2) Logistic	(3) OLS	(4) Logistic	(5) OLS	(6) Logistic	(7) OLS	(8) Logistic
Models using Combined Strategy variable:								
Past Account Creation	0.191*	3.190*	-0.0476	0.759	0.158***	11.84**	0.0471	2.117
	(0.107)	(1.957)	(0.0655)	(0.298)	(0.0479)	(13.55)	(0.0636)	(2.233)
Sample Size:								
N. Treatment	72	59	227	227	266	247	239	238
N. Non-Intent (control)	72	60	187	187	192	192	133	133
Model Observations	152	127	453	453	536	517	468	467
R-Squared (Pseudo)	0.302	0.180	0.163	0.163	0.178	0.224	0.201	0.248
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 45b.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation: Binary Individual Savings Components Nested in Treatment Strategy: by Household Income: any Postsecondary Institution Type

	Post-Match, Weighted Regressions							
	Reported Household Income							
	Income Q1		Income Q2		Income Q3		Income Q4	
Models	($0-25,000)		($25,001-50,000)		($50,001-75,000)		($75,001-100,000)	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	0.124	2.419	-0.00919	1.089	0.0654*	2.206**	0.0118	0.817
	(0.0976)	(1.393)	(0.0478)	(0.401)	(0.0382)	(0.856)	(0.0439)	(0.585)
Insurance	0.0170	1.030	-0.0728	0.509	0.0644	2.163	0.00723	1.437
	(0.123)	(0.639)	(0.0560)	(0.220)	(0.0431)	(1.309)	(0.0391)	(0.857)
U.S. Bonds	0.136	3.047	0.0591	1.785	0.00787	1.149	0.0279	1.557
	(0.101)	(2.675)	(0.0549)	(0.893)	(0.0411)	(0.495)	(0.0348)	(1.073)
Stock/Real Estate	-0.0286	0.655	0.0259	1.296	-0.00381	1.084	-0.00356	0.960
	(0.169)	(0.889)	(0.0498)	(0.538)	(0.0368)	(0.454)	(0.0366)	(0.583)
Other Savings	0.0436	1.012	-0.159**	0.275***	-0.113**	0.411*	0.0165	1.236
	(0.152)	(0.779)	(0.0620)	(0.117)	(0.0513)	(0.187)	(0.0386)	(0.945)
529 plan	0.00609	1.125	-5.70e-05	1.147	0.0696*	2.844**	0.0806**	4.459**
	(0.132)	(0.989)	(0.0526)	(0.480)	(0.0362)	(1.298)	(0.0335)	(2.658)
Sample Size:								
N. Savings	51	43	160	160	193	185	166	166
N. Insurance	20	18	71	71	73	67	71	71
N. U.S. Bonds	18	14	65	65	93	87	99	99
N. Stock/Real Estate	14	11	87	87	137	122	153	152
N. Other Savings	11	10	51	51	56	55	52	52
N. 529 plan	16	11	81	81	125	112	131	130
Model Observations	152	127	453	453	536	517	468	467
R-Squared (Pseudo)	0.304	0.185	0.179	0.185	0.187	0.236	0.213	0.275
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 46a.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation: Binary Treatment Variable: by Student's Postsecondary Enrollment Expectations: any Postsecondary Institution Type

	Post-Match, Weighted Regressions					
	Student's Postsecondary Expectations					
	Unsure		Enroll in College		≥ 4-yr degree	
Models	(1)	(2)	(3)	(4)	(5)	(6)
(Std. Error)	OLS	Logistic	OLS	Logistic	OLS	Logistic
Past Account Creation	0.0167	1.357	0.0298	1.496	0.0264	1.486
	(0.132)	(0.980)	(0.0298)	(0.513)	(0.0292)	(0.521)
Sample Size:						
N. Treatment	84	79	1,041	1,041	991	991
N. Non-Intent (control)	53	53	659	659	626	626
Model Observations	157	152	2,093	2,093	2,001	2,001
R-Squared (Pseudo)	0.316	0.263	0.181	0.230	0.164	0.219
Models conditioned on:						
pscores	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 46b.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation: Binary Individual Savings Components Nested in Treatment Strategy: by Student's Postsecondary Enrollment Expectations: any Postsecondary Institution Type

	Post-Match, Weighted Regressions					
	Student's Postsecondary Expectations					
	Unsure		Enroll in College		≥ 4-yr degree	
Models	(1)	(2)	(3)	(4)	(5)	(6)
(Std. Error)	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	-0.108	0.514	0.0158	1.340	0.0175	1.395
	(0.110)	(0.370)	(0.0189)	(0.332)	(0.0186)	(0.364)
Insurance	0.0815	1.969	0.00882	1.111	0.00476	1.044
	(0.100)	(1.326)	(0.0191)	(0.318)	(0.0191)	(0.315)
U.S. Bonds	0.0895	2.217	0.0257	1.624	0.0212	1.591
	(0.110)	(1.649)	(0.0171)	(0.484)	(0.0170)	(0.514)
Stock/Real Estate	0.125	2.070	-0.00890	0.879	-0.00946	0.851
	(0.104)	(1.286)	(0.0183)	(0.230)	(0.0182)	(0.236)
Other Savings	-0.242*	0.192*	-0.0299	0.609*	-0.0315	0.586*
	(0.123)	(0.186)	(0.0206)	(0.168)	(0.0210)	(0.173)
529 plan	0.136	2.716*	0.0215	1.470	0.0307**	1.858**
	(0.101)	(1.546)	(0.0160)	(0.393)	(0.0153)	(0.546)
Sample Size:						
N. Savings	59	56	730	730	696	696
N. Insurance	29	29	298	298	284	284
N. U.S. Bonds	29	27	363	363	342	342
N. Stock/Real Estate	37	34	575	575	557	557
N. Other Savings	18	18	232	232	221	221
N. 529 plan	43	39	513	513	487	487
Model Observations	157	152	2,093	2,093	2,001	2,001
R-Squared (Pseudo)	0.358	0.312	0.183	0.236	0.168	0.228
Models conditioned on:						
pscores	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 47a.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation: Binary Treatment Variable: by Postsecondary Institution Type

	Post-Match, Weighted Regressions							
	Enrolled Institution Type (Observed)							
Models	2-yr Institution		4-yr Institution		Public, 4-yr Institution		Private, 4-yr Institution	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Past Account Creation	0.0142	1.075	0.0321	1.230	-0.00716	0.954	0.0421	1.286
	(0.0371)	(0.219)	(0.0373)	(0.268)	(0.0386)	(0.191)	(0.0364)	(0.279)
Sample Size:								
N. Treatment	1,125	1,125	1,125	1,125	1,122	1,107	1,122	1,118
N. Non-Intent (control)	712	712	712	712	710	697	710	705
Model Observations	2,250	2,250	2,250	2,250	2,245	2,214	2,245	2,234
R-Squared (Pseudo)	0.076	0.071	0.274	0.227	0.105	0.080	0.069	0.070
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 47b.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation: Binary Individual Savings Components Nested in Treatment Strategy: by Postsecondary Institution Type

	Post-Match, Weighted Regressions Enrolled Institution Type (Observed)							
Models	2-yr Institution		4-yr Institution		Public, 4-yr Institution		Private, 4-yr Institution	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	-0.00560	0.952	0.0212	1.150	0.0232	1.107	0.00729	1.025
	(0.0258)	(0.142)	(0.0254)	(0.173)	(0.0280)	(0.149)	(0.0240)	(0.162)
Insurance	0.0230	1.145	-0.0121	0.955	-0.0515*	0.793	0.0329	1.221
	(0.0273)	(0.181)	(0.0269)	(0.154)	(0.0312)	(0.119)	(0.0266)	(0.201)
U.S. Bonds	0.0133	1.075	0.0176	1.138	0.00708	1.031	0.00389	1.026
	(0.0259)	(0.164)	(0.0256)	(0.177)	(0.0297)	(0.144)	(0.0252)	(0.164)
Stock/Real Estate	-0.0109	0.929	0.00669	1.057	0.0189	1.087	-0.00504	0.978
	(0.0258)	(0.140)	(0.0262)	(0.163)	(0.0294)	(0.149)	(0.0249)	(0.157)
Other Savings	0.00259	1.023	-0.0422	0.762	-0.0452	0.814	-0.00550	0.976
	(0.0292)	(0.181)	(0.0295)	(0.132)	(0.0335)	(0.129)	(0.0291)	(0.179)
529 plan	-0.0174	0.894	0.0501**	1.386**	0.00941	1.045	0.0472*	1.362**
	(0.0247)	(0.132)	(0.0248)	(0.205)	(0.0286)	(0.139)	(0.0243)	(0.207)
Sample Size:								
N. Savings	789	789	789	789	787	773	787	785
N. Insurance	327	327	327	327	325	320	325	324
N. U.S. Bonds	392	392	392	392	392	387	392	391
N. Stock/Real Estate	612	612	612	612	610	606	610	608
N. Other Savings	250	250	250	250	250	247	250	249
N. 529 plan	556	556	556	556	554	547	554	551
Model Observations	2,250	2,250	2,250	2,250	2,245	2,214	2,245	2,234
R-Squared (Pseudo)	0.077	0.071	0.277	0.230	0.108	0.082	0.072	0.072
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 48a.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Treatment Variable: any Postsecondary Institution Type

	Naïve, Unweighted		Matched	Post- Match, Weighted Regressions					
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Std. Error)	OLS	Logistic		OLS	Logistic	OLS	Logistic	OLS	Logistic
Past Account Creation +	0.181***	2.859***	0.0339	0.0338	1.331	0.0349	1.510*	0.0955**	4.471**
Past Asset Reallocation	(0.0164)	(0.358)	(0.0244)	(0.0233)	(0.258)	(0.0221)	(0.343)	(0.0421)	(2.672)
Sample Size:									
N. Treatment	548	548	443	443	443	443	443	405	375
N. Non-Intent (control)	5,107	5,107	3,611	372	372	372	372	352	352
Model Observations	5,655	5,655	4,054	886	886	886	886	821	791
R-Squared (Pseudo)	0.013	0.012	n.a.	0.089	0.126	0.217	0.289	0.348	0.403
Models conditioned on:									
pscores	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	No	No	Yes	Yes	Yes	Yes
Amount Saved & GPA	No	No	No	No	No	No	No	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 48b.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Individual Savings Components Nested in Treatment Strategy: any Postsecondary Institution Type

	Naïve, Unweighted		Matched	Post- Match, Weighted Regressions					
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Std. Error)	OLS	Logistic		OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	-0.0140	0.805	n.a.	-0.0596*	0.585*	-0.0456	0.607	-0.0425	0.496
	(0.0310)	(0.211)	n.a.	(0.0321)	(0.186)	(0.0302)	(0.220)	(0.0311)	(0.233)
Insurance	-0.0374	0.722	n.a.	-0.0521	0.633	-0.0338	0.689	-0.0196	0.783
	(0.0326)	(0.185)	n.a.	(0.0344)	(0.192)	(0.0315)	(0.245)	(0.0307)	(0.354)
U.S. Bonds	0.0793***	1.864**	n.a.	0.0684**	1.787*	0.0452	1.542	0.0495*	1.872
	(0.0295)	(0.501)	n.a.	(0.0307)	(0.572)	(0.0293)	(0.559)	(0.0274)	(0.827)
Stock/Real Estate	0.0859***	1.868***	n.a.	0.0399	1.375	0.0159	1.260	-0.00596	0.986
	(0.0285)	(0.436)	n.a.	(0.0304)	(0.392)	(0.0278)	(0.410)	(0.0291)	(0.405)
Other Savings	-0.0403	0.725	n.a.	-0.0845**	0.508**	-0.0643*	0.394***	-0.0167	0.642
	(0.0338)	(0.181)	n.a.	(0.0360)	(0.151)	(0.0344)	(0.131)	(0.0304)	(0.245)
529 plan	0.0637**	1.642*	n.a.	0.0169	1.183	0.0163	1.178	0.0200	1.114
	(0.0291)	(0.430)	n.a.	(0.0298)	(0.353)	(0.0282)	(0.399)	(0.0294)	(0.518)
Add Job	0.0909***	1.908**	n.a.	0.0335	1.527	0.0370	1.793*	0.0289	1.962
	(0.0284)	(0.487)	n.a.	(0.0304)	(0.457)	(0.0283)	(0.625)	(0.0306)	(1.024)
Reduce Expenses	0.0713**	1.610*	n.a.	0.0523*	1.723*	0.0482*	2.120**	0.0387	2.293*
	(0.0278)	(0.401)	n.a.	(0.0301)	(0.508)	(0.0285)	(0.737)	(0.0281)	(1.146)
Remortgage	0.0884**	2.033	n.a.	0.0571	1.794	0.0381	1.639	0.0374	2.547
	(0.0386)	(0.901)	n.a.	(0.0430)	(0.930)	(0.0414)	(0.883)	(0.0393)	(1.741)
Sample Size:									
N. Savings	426	426	346	346	346	346	346	315	296
N. Insurance	204	204	167	167	167	167	167	153	140
N. U.S. Bonds	228	228	185	185	185	185	185	171	159
N. Stock/Real Estate	302	302	242	242	242	242	242	227	200
N. Other Savings	169	169	137	137	137	137	137	120	112
N. 529 plan	212	212	179	179	179	179	179	166	148
N. Add Job	273	273	226	226	226	226	226	207	191
N. Reduce Expenses	339	339	269	269	269	269	269	246	231
N. Remortgage	73	73	59	59	59	59	59	53	48
Model Observations	5,655	5,655	4,054	886	886	886	886	821	791
(Pseudo) R-Squared	0.015	0.015	n.a.	0.107	0.146	0.251	0.303	0.349	0.406
Models conditioned on:									
pscores	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	No	No	Yes	Yes	Yes	Yes
Amount Saved & GPA	No	No	No	No	No	No	No	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 49a.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Treatment Variable: by Gender and Race and Ethnicity: any Postsecondary Institution Type

	Post-Match, Weighted Regressions									
	Student's Gender				*Student's Race and Ethnicity*					
Models	Male		Female		White		African-American		Hispanic	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Past Account Creation +	0.0734	2.326	0.0975*	3.327	0.0974**	3.355*	0.0652	1.808	-0.240*	1.17e-08***
Past Asset Reallocation	(0.0640)	(1.621)	(0.0578)	(2.601)	(0.0432)	(2.088)	(0.162)	(2.344)	(0.138)	(1.66e-08)
Sample Size:										
N. Treatment	175	168	230	207	292	268	39	28	29	17
N. Non-Intent (control)	178	178	238	238	244	244	37	32	33	29
Model Observations	353	346	468	445	578	554	93	76	64	48
R-Squared (Pseudo)	0.332	0.337	0.205	0.269	0.219	0.268	0.519	0.487	0.382	0.245
Models conditioned on:										
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 49b.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Individual Savings Components Nested in Treatment Strategy: by Gender and Race and Ethnicity: any Postsecondary Institution Type

	Post-Match, Weighted Regressions									
	Student's Gender				*Student's Race and Ethnicity*					
Models	Male		Female		White		African-American		Hispanic	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	-0.00799	0.885	-0.0722*	0.298	-0.0401	0.515	0.201	6.41e+30***	0.0746	*0*
	(0.0530)	(0.608)	(0.0397)	(0.224)	(0.0322)	(0.224)	(0.148)	(1.185e+31)	(0.220)	*(0)*
Insurance	-0.0923*	0.293**	-0.00835	0.805	-0.0253	0.653	-0.160	*3.74e-07*	-0.212*	*0*
	(0.0515)	(0.170)	(0.0405)	(0.473)	(0.0339)	(0.330)	(0.111)	*(0)*	(0.125)	*(0)*
U.S. Bonds	0.0915*	3.229*	0.0222	1.247	0.0648**	3.003**	-0.172	*0*	*0*	*0*
	(0.0468)	(2.051)	(0.0346)	(0.800)	(0.0306)	(1.470)	(0.122)	*(0)*	*(0)*	*(0)*
Stock/Real Estate	0.0127	1.002	0.000442	1.012	-0.000904	1.046	0.268	*1.065e+50*	0.277	*0*
	(0.0458)	(0.557)	(0.0344)	(0.568)	(0.0311)	(0.437)	(0.188)	*(0)*	(0.204)	*(0)*
Other Savings	-0.103*	0.331**	0.0284	2.055	-0.0415	0.656	0.0959	3.14e-09***	-0.302	*0*
	(0.0540)	(0.171)	(0.0368)	(1.291)	(0.0378)	(0.307)	(0.122)	(6.61e-09)	(0.295)	*(0)*
529 plan	-0.00729	0.997	0.0447	1.802	0.0342	2.288	0.0344	3.29e+18***	0.733**	*0*
	(0.0480)	(0.605)	(0.0357)	(1.175)	(0.0287)	(1.430)	(0.111)	(1.058e+19)	(0.276)	*(0)*
Add Job	0.0215	1.735	0.0398	2.330	0.0269	1.334	-0.296*	*0*	-0.582**	*0*
	(0.0439)	(0.912)	(0.0450)	(2.264)	(0.0316)	(0.633)	(0.169)	*(0)*	(0.240)	*(0)*
Reduce Expenses	0.0538	2.345	0.0402	2.587	0.0363	1.685	-0.173	*0*	-0.450	*0*
	(0.0424)	(1.315)	(0.0408)	(2.436)	(0.0296)	(0.767)	(0.162)	*(0)*	(0.268)	*(0)*
Remortgage	-0.0186	0.854	0.133***	*0*	0.00942	1.281	*0*	*0*	*0*	*0*
	(0.0702)	(0.547)	(0.0400)	*(0)*	(0.0478)	(0.706)	*(0)*	*(0)*	*(0)*	*(0)*
Sample Size:										
N. Savings	144	139	171	142	228	212	31	20	24	12
N. Insurance	63	61	90	71	103	92	21	16	12	6
N. U.S. Bonds	75	72	96	80	138	127	13	9	5	3
N. Stock/Real Estate	104	97	123	89	178	155	12	6	15	5
N. Other Savings	52	51	68	57	76	71	13	6	11	5
N. 529 plan	72	67	94	72	114	98	19	11	10	5
N. Add Job	97	93	110	89	149	137	16	12	19	8
N. Reduce Expenses	96	93	150	128	182	170	26	15	12	7
N. Remortgage	27	26	26	0	40	36	3	0	3	0
Model Observations	353	346	468	423	578	554	93	73	64	45
R-Squared (Pseudo)	0.347	0.362	0.217	0.289	0.224	0.285	0.616	0.789	491	0.474
Models conditioned on:										
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Models with zero standard error values have insufficient observations to repost coefficient estimates. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 50a.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Treatment Variable: by Household Income: any Postsecondary Institution Type

	Post-Match, Weighted Regressions							
	Reported Household Income							
Models	Income Q1 ($0-25,000)		Income Q2 ($25,001-50,000)		Income Q3 ($50,001-75,000)		Income Q4 ($75,001-100,000)	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Past Account Creation +	0.144	3.059	0.0911	2.444	0.0323	0.930	0.125**	3.708e+06***
Past Asset Reallocation	(0.125)	(2.538)	(0.0988)	(2.213)	(0.0675)	(1.026)	(0.0553)	(3.520e+06)
Sample Size:								
N. Treatment	35	28	92	90	99	48	83	43
N. Non-Intent (control)	42	33	80	80	90	70	71	71
Model Observations	79	62	177	175	205	129	170	130
R-Squared (Pseudo)	0.423	0.212	0.270	0.242	0.250	0.204	0.222	0.253
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 50b.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Individual Savings Components Nested in Treatment Strategy: by Household Income: any Postsecondary Institution Type

	Post-Match, Weighted Regressions							
	Reported Household Income							
	Income Q1		Income Q2		Income Q3		Income Q4	
Models	($0-25,000)		($25,001-50,000)		($50,001-75,000)		($75,001-100,000)	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	-0.0625	0.732	-0.0586	0.721	0.0101	0.849	0.0387	*0*
	(0.150)	(1.372)	(0.101)	(0.460)	(0.0438)	(0.689)	(0.0510)	*(0)*
Insurance	0.0377	*0*	-0.105	0.427	-0.00548	0.931	-0.0934	0.478
	(0.203)	*(0)*	(0.0978)	(0.322)	(0.0474)	(0.749)	(0.0680)	(1.832)
U.S. Bonds	0.475***	*0*	0.174**	3.237*	-0.0139	0.673	0.0853	5.433e+24***
	(0.145)	*(0)*	(0.0719)	(1.960)	(0.0517)	(0.562)	(0.0538)	(1.387e+25)
Stock/Real Estate	0.588**	*0*	-0.00136	1.034	-0.0269	0.419	-0.190**	*0*
	(0.221)	*(0)*	(0.0718)	(0.549)	(0.0489)	(0.333)	(0.0735)	*(0)*
Other Savings	0.0804	*0*	-0.189*	0.242**	0.0334	1.226	0.0552	*0*
	(0.184)	*(0)*	(0.0971)	(0.155)	(0.0465)	(0.967)	(0.0601)	*(0)*
529 plan	-0.00246	*0*	-0.120	0.361	0.0470	4.253*	0.0473	3.434e+13***
	(0.183)	*(0)*	(0.0961)	(0.268)	(0.0426)	(3.742)	(0.0526)	(1.733e+14)
Add Job	-0.000940	0.167	-0.0353	0.779	0.0101	1.224	0.120**	7.811e+96***
	(0.184)	(0.298)	(0.0870)	(0.596)	(0.0322)	(0.846)	(0.0491)	(1.601e+97)
Reduce Expenses	-0.195	0.00665**	0.0672	2.122	0.00919	1.431	0.105**	1.128e+83***
	(0.141)	(0.0133)	(0.0831)	(1.593)	(0.0495)	(1.272)	(0.0496)	(3.244e+83)
Remortgage	-0.617*	*0*	0.247***	7.711**	-0.0535	*0*	0.165*	*0*
	(0.322)	*(0)*	(0.0883)	(6.261)	(0.0922)	*(0)*	(0.0835)	*(0)*
Sample Size:								
N. Savings	21	13	75	74	75	38	71	38
N. Insurance	12	8	42	40	33	16	31	16
N. U.S. Bonds	7	0	38	37	41	21	39	20
N. Stock/Real Estate	7	0	46	44	56	25	51	23
N. Other Savings	17	9	20	20	28	13	21	13
N. 529 plan	12	7	23	22	42	22	39	19
N. Add Job	20	12	46	45	52	20	37	19
N. Reduce Expenses	21	13	59	58	65	36	52	26
N. Remortgage	2	0	11	11	12	7	13	5
Model Observations	79	54	177	175	205	129	170	130
R-Squared (Pseudo)	0.516	0.350	0.320	0.300	0.255	0.232	0.275	0.502
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Models with zero standard error values have insufficient observations to repost coefficient estimates. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 51a.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Treatment Variable: by Student's Postsecondary Enrollment Expectations: any Postsecondary Institution Type

	Post-Match, Weighted Regressions					
	Student's Postsecondary Expectations					
Models	Unsure		Enroll in College		≥ 4-yr degree	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Logistic	OLS	Logistic	OLS	Logistic
Past Account Creation + Past Asset Reallocation	-0.0370	0.720	0.0864**	3.159*	0.0829**	3.208*
	(0.149)	(0.626)	(0.0419)	(1.868)	(0.0406)	(2.224)
Sample Size:						
N. Treatment	37	35	368	338	354	324
N. Non-Intent (control)	34	34	318	318	297	297
Model Observations	74	72	747	717	711	681
R-Squared (Pseudo)	0.374	0.287	0.232	0.284	0.206	0.276
Models conditioned on:						
pscores	Yes	Yes	Yes	Yes	Yes	Yes
Amount saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 51b.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Individual Savings Components Nested in Treatment Strategy: by Student's Postsecondary Enrollment Expectations: any Postsecondary Institution Type

	Post-Match, Weighted Regressions					
	Student's Postsecondary Expectations					
Models	Unsure		Enroll in College		≥ 4-yr degree	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	0.0608	*0*	-0.0447	0.537	-0.0425	0.569
	(0.173)	*(0)*	(0.0274)	(0.244)	(0.0261)	(0.300)
Insurance	-0.240	*0*	-0.0181	0.717	-0.0157	0.680
	(0.170)	*(0)*	(0.0307)	(0.323)	(0.0297)	(0.338)
U.S. Bonds	0.327*	*0*	0.0305	1.541	0.0225	1.373
	(0.191)	*(0)*	(0.0266)	(0.692)	(0.0259)	(0.710)
Stock/Real Estate	-0.178	*0*	0.0198	1.610	0.0143	1.636
	(0.147)	*(0)*	(0.0289)	(0.713)	(0.0286)	(0.814)
Other Savings	-0.250	*0*	-0.0249	0.787	-0.0377	0.583
	(0.156)	*(0)*	(0.0301)	(0.337)	(0.0299)	(0.283)
529 plan	0.0540	3.336	0.0294	1.723	0.0509**	2.797**
	(0.137)	(49.03)	(0.0274)	(0.761)	(0.0250)	(1.456)
Add Job	0.367**	9.262e+168***	0.0234	1.518	0.0238	1.796
	(0.182)	(1.649e+170)	(0.0286)	(0.704)	(0.0283)	(0.930)
Reduce Expenses	-0.0213	1.302e+54***	0.0408	1.727	0.0309	1.549
	(0.133)	(1.163e+55)	(0.0278)	(0.810)	(0.0270)	(0.865)
Remortgage	*0*	*0*	0.00957	1.245	0.0375	2.570
	(0)	*(0)*	(0.0362)	(0.697)	(0.0325)	(1.982)
Sample Size:						
N. Savings	29	29	286	267	277	258
N. Insurance	18	18	135	122	130	117
N. U.S. Bonds	14	14	157	145	153	141
N. Stock/Real Estate	17	17	210	183	203	176
N. Other Savings	11	9	109	101	103	95
N. 529 plan	11	10	155	137	151	133
N. Add Job	22	21	185	169	180	164
N. Reduce Expenses	21	20	225	210	215	200
N. Remortgage	5	5	48	43	46	41
Model Observations	74	72	747	717	711	681
R-Squared (Pseudo)	0.448	0.601	0.235	0.291	0.211	0.291
Models conditioned on:						
pscores	Yes	Yes	Yes	Yes	Yes	Yes
Amount saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Models with zero standard error values have insufficient observations to repost coefficient estimates. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 52a.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Treatment Variable: by Postsecondary Institution Type

Models (Std. Error)	*Post-Match, Weighted Regression* *Enrolled Institution Type (Observed)* 2-yr Institution		4-yr Institution		Public, 4-yr Institution		Private, 4-yr Institution	
	(1) OLS	(2) Logistic	(3) OLS	(4) Logistic	(5) OLS	(6) Logistic	(7) OLS	(8) Logistic
Past Account Creation + Past Asset Reallocation	0.00726 (0.0607)	1.036 (0.367)	0.0894 (0.0585)	1.628 (0.583)	0.0118 (0.0674)	1.046 (0.351)	0.0641 (0.0624)	1.511 (0.566)
Sample Size:								
N. Treatment	405	405	405	405	404	397	404	397
N. Non-Intent (control)	352	352	352	352	351	342	351	342
Model Observations	821	821	821	821	819	800	819	800
R-Squared (Pseudo)	0.072	0.068	0.280	0.230	0.102	0.080	0.118	0.115
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 52b.

Propensity Score Matching Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation: Binary Individual Savings Components Nested in Treatment Strategy: by Postsecondary Institution Type

	Post-Match, Weighted Regression Enrolled Institution Type (Observed)							
Models	2-yr Institution		4-yr Institution		Public, 4-yr Institution		Private, 4-yr Institution	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	-0.0490	0.752	-0.00626	0.938	0.0207	1.087	-0.0452	0.765
	(0.0486)	(0.209)	(0.0493)	(0.271)	(0.0536)	(0.290)	(0.0499)	(0.243)
Insurance	4.08e-05	1.015	-0.0538	0.699	-0.0781	0.680	0.0232	1.168
	(0.0431)	(0.264)	(0.0438)	(0.186)	(0.0477)	(0.162)	(0.0410)	(0.324)
U.S. Bonds	0.00529	1.027	0.0478	1.372	0.0340	1.210	-0.000767	0.953
	(0.0418)	(0.259)	(0.0412)	(0.340)	(0.0475)	(0.275)	(0.0408)	(0.255)
Stock/Real Estate	0.0144	1.134	-0.0140	0.860	-0.0110	0.938	0.0157	1.144
	(0.0443)	(0.307)	(0.0428)	(0.219)	(0.0481)	(0.219)	(0.0419)	(0.332)
Other Savings	0.106**	1.921**	-0.121***	0.485***	-0.0444	0.803	-0.0624	0.632
	(0.0474)	(0.515)	(0.0462)	(0.135)	(0.0503)	(0.201)	(0.0415)	(0.187)
529 plan	0.0882*	1.658*	-0.0391	0.776	0.0441	1.243	-0.0840**	0.537**
	(0.0459)	(0.445)	(0.0456)	(0.210)	(0.0482)	(0.288)	(0.0417)	(0.161)
Add Job	-0.0397	0.696	0.0814*	1.745*	0.0108	1.036	0.0792*	1.636*
	(0.0460)	(0.207)	(0.0460)	(0.499)	(0.0520)	(0.260)	(0.0440)	(0.439)
Reduce Expenses	0.00503	0.940	0.0494	1.419	-0.0457	0.792	0.100**	1.934**
	(0.0444)	(0.272)	(0.0428)	(0.385)	(0.0498)	(0.193)	(0.0437)	(0.532)
Remortgage	-0.126**	0.429**	0.127**	2.459**	0.0623	1.348	0.00760	0.990
	(0.0563)	(0.179)	(0.0611)	(0.955)	(0.0676)	(0.430)	(0.0592)	(0.393)
Sample Size:								
N. Savings	315	315	315	315	314	308	314	308
N. Insurance	153	153	153	153	152	147	152	147
N. U.S. Bonds	171	171	171	171	171	167	171	167
N. Stock/Real Estate	227	227	227	227	226	223	226	223
N. Other Savings	120	120	120	120	120	118	120	118
N. 529 plan	166	166	166	166	166	162	166	162
N. Add Job	207	207	207	207	206	203	206	203
N. Reduce Expenses	246	246	246	246	246	242	246	242
N. Remortgage	53	53	53	53	53	52	53	52
Model Observations	821	821	821	821	819	800	819	800
R-Squared (Pseudo)	0.088	0.084	0.290	0.242	0.109	0.086	0.132	0.131
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 53a.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Treatment Variable: any Postsecondary Institution Type

	Naïve, Unweighted		Matched	Post- Match, Weighted Regressions					
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Std. Error)	OLS	Logistic		OLS	Logistic	OLS	Logistic	OLS	Logistic
Past Account Creation + Past Asset Reallocation + Future Intention	0.188*** (0.00991)	3.032*** (0.211)	0.0487*** (0.0146)	0.0487*** (0.0121)	1.492*** (0.147)	0.0499*** (0.0116)	1.613*** (0.173)	0.0302 (0.0223)	1.322 (0.326)
Sample Size:									
N. Treatment	2,138	2,138	1,683	1,683	1,683	1,683	1,683	1,589	1,589
N. Non-Intent (control)	5,107	5,107	3,917	1,081	1,081	1,081	1,081	1,003	1,003
Model Observations	7,245	7,245	5,600	3,366	3,366	3,366	3,366	3,150	3,150
R-Squared (Pseudo)	0.037	0.350	n.a.	0.101	0.120	0.020	0.221	0.272	0.324
Models conditioned on:									
pscores	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	No	No	Yes	Yes	Yes	Yes
Amount Saved & GPA	No	No	No	No	No	No	No	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 53b.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Individual Savings Components Nested in Treatment Strategy: any Postsecondary Institution Type

	Naïve, Unweighted		Matched	Post- Match, Weighted Regressions					
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Std. Error)	OLS	Logistic		OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	0.00985	1.039	n.a.	-0.0120	0.905	-0.00710	0.952	-0.0182	0.810
	(0.0176)	(0.150)	n.a.	(0.0185)	(0.150)	(0.0177)	(0.172)	(0.0174)	(0.169)
Insurance	-0.0256*	0.803*	n.a.	-0.0165	0.848	-0.00499	0.910	-0.00506	0.901
	(0.0155)	(0.102)	n.a.	(0.0165)	(0.124)	(0.0159)	(0.143)	(0.0157)	(0.162)
U.S. Bonds	0.0493***	1.538***	n.a.	0.0447***	1.516**	0.0394**	1.537**	0.0293*	1.445*
	(0.0148)	(0.214)	n.a.	(0.0157)	(0.247)	(0.0155)	(0.272)	(0.0150)	(0.283)
Stock/Real Estate	0.0579***	1.602***	n.a.	-0.00836	0.964	-0.0203	0.919	-0.0244	0.811
	(0.0148)	(0.204)	n.a.	(0.0160)	(0.141)	(0.0153)	(0.147)	(0.0154)	(0.154)
Other Savings	0.00562	1.045	n.a.	0.0262	1.270	0.0415***	1.356*	0.0421***	1.450**
	(0.0154)	(0.137)	n.a.	(0.0164)	(0.192)	(0.0156)	(0.219)	(0.0154)	(0.268)
529 plan	0.0414***	1.418**	n.a.	0.00644	1.148	0.000396	1.106	0.0121	1.230
	(0.0148)	(0.193)	n.a.	(0.0158)	(0.180)	(0.0149)	(0.184)	(0.0149)	(0.248)
Add Job	0.00205	0.995	n.a.	-0.00429	0.932	-0.0166	0.809	-0.0191	0.742*
	(0.0155)	(0.131)	n.a.	(0.0167)	(0.139)	(0.0160)	(0.131)	(0.0157)	(0.134)
Reduce Expenses	0.0294	1.202	n.a.	0.0147	1.133	0.00694	1.107	-0.0100	0.961
	(0.0207)	(0.199)	n.a.	(0.0220)	(0.222)	(0.0216)	(0.233)	(0.0211)	(0.239)
Remortgage	0.0261	1.251	n.a.	-3.20e-05	1.055	0.0111	1.103	-0.00147	0.920
	(0.0183)	(0.220)	n.a.	(0.0196)	(0.213)	(0.0192)	(0.250)	(0.0191)	(0.239)
Plan to Reduce Expenses	0.0882***	1.578**	n.a.	0.0240	1.188	0.0345	1.331	0.0322	1.418
	(0.0251)	(0.311)	n.a.	(0.0273)	(0.286)	(0.0263)	(0.342)	(0.0268)	(0.464)
Plan to Remortgage	0.0197	1.118	n.a.	0.0107	1.121	-0.000973	0.995	-0.00247	0.989
	(0.0171)	(0.167)	n.a.	(0.0182)	(0.197)	(0.0174)	(0.189)	(0.0173)	(0.216)
Sample Size:									
N. Savings	1,709	1,709	1,335	1,335	1,335	1,335	1,335	1,251	1,251
N. Insurance	879	879	689	689	689	689	689	645	645
N. U.S. Bonds	777	777	626	626	626	626	626	588	588
N. Stock/Real Estate	1,084	1,084	875	875	875	875	875	827	827
N. Other Savings	783	783	619	619	619	619	619	578	578
N. 529 plan	780	780	623	623	623	623	623	588	588
N. Add Job	851	851	669	669	669	669	669	634	634
N. Reduce Expenses	1,815	1,815	1,432	1,432	1,432	1,432	1,432	1,355	1,355
N. Remortgage	400	400	309	309	309	309	309	292	292
N. Plan to Reduce Exp.	2,040	2,040	1,605	1,605	1,605	1,605	1,605	406	406
N. Plan to Remortgage	541	541	427	427	427	427	427	1,003	1,003
Model Observations	7,245	7,245	5,600	3,366	3,366	3,366	3,366	3,150	3,150
R-Squared (Pseudo)	0.038	0.038	n.a.	0.103	0.123	0.201	0.224	0.275	0.328
Models conditioned on:									
pscores	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	No	No	Yes	Yes	Yes	Yes
Amount Saved & GPA	No	No	No	No	No	No	No	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 54a.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Treatment Variable: by Gender and Race and Ethnicity: any Postsecondary Institution Type

	Post-Match, Weighted Regression									
	Student's Gender				*Student's Race and Ethnicity*					
Models	Male		Female		White		African-American		Hispanic	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Past Account Creation + Past Asset Reallocation + Future Intention	0.0122 (0.0355)	0.913 (0.349)	0.0348 (0.0312)	1.486 (0.476)	0.0546* (0.0292)	1.993* (0.835)	0.00321 (0.0600)	0.983 (0.515)	0.0249 (0.0712)	1.169 (0.559)
Sample Size:										
N. Treatment	789	789	800	800	987	982	201	187	162	153
N. Non-Intent (control)	787	787	774	774	614	613	119	111	134	133
Model Observations	1,576	1,576	1,574	1,574	1,942	1,936	403	379	339	329
R-Squared (Pseudo)	0.267	0.308	0.180	0.235	0.246	0.298	0.211	0.176	0.19	0.166
Models conditioned on:										
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 54b.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Individual Savings Components Nested in Treatment Strategy: by Gender and Race and Ethnicity: any Postsecondary Institution Type

	Post-Match, Weighted Regression									
	Student's Gender				*Student's Race and Ethnicity*					
Models	Male		Female		White		African-American		Hispanic	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	-0.0194	0.874	-0.0338	0.670	-0.0170	0.896	0.00981	1.024	0.00524	1.106
	(0.0252)	(0.233)	(0.0250)	(0.203)	(0.0210)	(0.239)	(0.0717)	(0.571)	(0.0669)	(0.596)
Insurance	-0.0131	0.856	-0.0152	0.845	0.00470	1.030	-0.0285	0.736	-0.0163	0.916
	(0.0228)	(0.214)	(0.0223)	(0.199)	(0.0193)	(0.232)	(0.0524)	(0.315)	(0.0728)	(0.479)
U.S. Bonds	0.0496**	1.777**	0.0222	1.332	0.0275	1.391	0.0926*	2.590*	0.0515	1.981
	(0.0216)	(0.477)	(0.0211)	(0.367)	(0.0185)	(0.334)	(0.0519)	(1.446)	(0.0640)	(1.336)
Stock/Real Estate	-0.0101	0.900	-0.0280	0.752	0.00711	1.158	-0.0938	0.420	-0.00949	0.864
	(0.0222)	(0.235)	(0.0221)	(0.194)	(0.0188)	(0.282)	(0.0598)	(0.231)	(0.0567)	(0.397)
Other Savings	0.0447**	1.590*	0.0264	1.276	0.0334*	1.442	0.00526	1.047	0.0128	1.089
	(0.0226)	(0.385)	(0.0220)	(0.334)	(0.0192)	(0.372)	(0.0550)	(0.454)	(0.0572)	(0.512)
529 plan	0.00572	1.166	0.0301	1.707*	0.0355**	1.763**	0.0131	1.051	-0.0606	0.690
	(0.0212)	(0.295)	(0.0227)	(0.543)	(0.0175)	(0.452)	(0.0527)	(0.468)	(0.0622)	(0.350)
Add Job	-0.0410*	0.590**	0.00720	1.016	-0.0166	0.740	-0.0179	0.985	0.0139	1.088
	(0.0228)	(0.145)	(0.0226)	(0.250)	(0.0191)	(0.167)	(0.0658)	(0.499)	(0.0567)	(0.525)
Reduce Expenses	-0.00145	1.115	-0.00714	0.936	-0.0229	0.765	0.115	2.275	0.0195	1.064
	(0.0303)	(0.380)	(0.0294)	(0.323)	(0.0236)	(0.228)	(0.0974)	(1.597)	(0.114)	(0.950)
Remortgage	0.0160	1.213	-0.0323	0.769	-0.0365	0.676	0.0287	1.225	0.00682	1.291
	(0.0265)	(0.435)	(0.0274)	(0.247)	(0.0233)	(0.206)	(0.0932)	(0.999)	(0.0706)	(0.839)
Plan to Reduce Expenses	-0.0123	0.553	0.0632	1.998*	0.0440	1.641	-0.108	0.446	0.0290	1.303
	(0.0375)	(0.271)	(0.0391)	(0.810)	(0.0291)	(0.640)	(0.118)	(0.456)	(0.143)	(1.203)
Plan to Remortgage	0.0527**	1.998**	-0.0246	0.790	0.0278	1.329	0.0272	1.259	-0.0219	0.728
	(0.0260)	(0.668)	(0.0237)	(0.206)	(0.0219)	(0.375)	(0.0685)	(0.713)	(0.0586)	(0.384)
Sample Size:										
N. Savings	615	615	636	636	768	765	169	156	115	107
N. Insurance	322	322	323	323	392	391	94	85	48	44
N. U.S. Bonds	307	307	281	281	411	410	66	64	35	30
N. Stock/Real Estate	418	418	409	409	544	540	88	79	69	62
N. Other Savings	301	301	277	277	317	316	83	79	83	77
N. 529 plan	305	305	283	283	376	374	70	64	43	39
N. Add Job	312	312	322	322	392	390	73	68	67	65
N. Reduce Expenses	671	671	684	684	823	818	177	165	142	134
N. Remortgage	140	140	152	152	188	188	21	19	33	32
N. Plan to Reduce Exp.	753	753	761	761	930	925	196	183	156	147
N. Plan to Remortgage	188	188	218	218	246	246	46	43	51	50
Model Observations	1,576	1,576	1,574	1,574	1,942	1,936	403	379	339	329
R-Squared (Pseudo)	0.273	0.321	0.187	0.246	0.249	0.304	0.228	0.201	0.13	0.172
Models conditioned on:										
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 55a.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Treatment Variable: by Household Income: any Postsecondary Institution Type

	Post-Match, Weighted Regression							
	Reported Household Income							
Models	Income Q1 ($0-25,000)		Income Q2 ($25,001-50,000)		Income Q3 ($50,001-75,000)		Income Q4 ($75,001-100,000)	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logistic	OLS	Logistic	OLS	Logistic	OLS	Logistic
Past Account Creation + Past Asset Reallocation + Future Intention	0.0160 (0.0856)	1.106 (0.502)	0.0939** (0.0444)	2.603* (1.366)	-0.0381 (0.0526)	0.687 (0.279)	0.0513*** (0.0163)	884,398*** (370,645)
Sample Size:								
N. Treatment	171	169	426	426	418	292	301	207
N. Non-Intent (control)	153	148	316	316	253	188	150	126
Model Observations	358	350	844	844	800	580	586	437
R-Squared (Pseudo)	0.238	0.19	0.193	0.198	0.216	0.165	0.147	0.198
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 55b.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Individual Savings Components Nested in Treatment Strategy: by Household Income: any Postsecondary Institution Type

	Post-Match, Weighted Regression							
	Reported Household Income							
Models	Income Q1 ($0-25,000)		Income Q2 ($25,001-50,000)		Income Q3 ($50,001-75,000)		Income Q4 ($75,001-100,000)	
(Std. Error)	(1) OLS	(2) Logistic	(3) OLS	(4) Logistic	(5) OLS	(6) Logistic	(7) OLS	(8) Logistic
Saving	-0.0129	0.941	0.000502	1.042	-0.0366	0.699	-0.0296	0.576
	(0.0846)	(0.450)	(0.0430)	(0.329)	(0.0329)	(0.346)	(0.0276)	(0.371)
Insurance	-0.0365	0.771	-0.0232	0.844	-0.00969	0.895	0.00313	0.873
	(0.0717)	(0.308)	(0.0381)	(0.224)	(0.0260)	(0.355)	(0.0270)	(0.549)
U.S. Bonds	0.0332	1.142	0.0131	1.117	0.0515**	2.306**	0.0278	1.677
	(0.0908)	(0.592)	(0.0379)	(0.332)	(0.0255)	(0.939)	(0.0229)	(1.010)
Stock/Real Estate	0.0158	1.169	-0.0366	0.774	-0.0146	0.750	-0.0561**	0.184*
	(0.0705)	(0.509)	(0.0375)	(0.215)	(0.0262)	(0.311)	(0.0256)	(0.164)
Other Savings	0.101	1.676	0.0424	1.367	0.0105	0.921	0.0119	0.994
	(0.0688)	(0.671)	(0.0375)	(0.388)	(0.0270)	(0.387)	(0.0253)	(0.734)
529 plan	0.0610	1.488	0.0192	1.284	0.0263	1.722	0.0153	2.422
	(0.0822)	(0.700)	(0.0376)	(0.384)	(0.0245)	(0.814)	(0.0241)	(1.610)
Add Job	-0.0631	0.687	-0.0416	0.655	0.0175	1.219	-0.00714	0.824
	(0.0684)	(0.279)	(0.0388)	(0.188)	(0.0262)	(0.516)	(0.0263)	(0.549)
Reduce Expenses	-0.0261	0.894	0.0173	1.147	-0.0258	0.778	0.00505	0.979
	(0.106)	(0.545)	(0.0563)	(0.453)	(0.0331)	(0.495)	(0.0297)	(0.633)
Remortgage	-0.221	0.310	0.00690	1.275	0.0397	2.906	-0.0214	0.593
	(0.153)	(0.248)	(0.0561)	(0.546)	(0.0301)	(2.016)	(0.0352)	(0.405)
Plan to Reduce Expenses	0.0269	1.176	0.0548	1.654	-0.00114	0.878	0.0706	5.605
	(0.134)	(0.936)	(0.0662)	(0.804)	(0.0531)	(0.782)	(0.0457)	(5.888)
Plan to Remortgage	0.0735	1.425	0.0300	1.227	-0.0414	0.564	-0.000163	1.768
	(0.0941)	(0.763)	(0.0431)	(0.385)	(0.0342)	(0.299)	(0.0273)	(1.457)
Sample Size:								
N. Savings	137	136	338	338	324	232	239	164
N. Insurance	63	62	177	177	176	128	138	94
N. U.S. Bonds	32	31	132	132	178	122	138	99
N. Stock/Real Estate	48	47	164	164	227	160	194	130
N. Other Savings	80	79	159	159	142	106	102	68
N. 529 plan	48	46	123	123	145	97	128	89
N. Add Job	77	75	187	187	156	103	118	74
N. Reduce Expenses	152	150	365	365	359	254	253	176
N. Remortgage	13	12	64	64	89	52	56	42
N. Plan to Reduce Exp.	167	165	412	412	396	280	284	194
N. Plan to Remortgage	31	30	91	91	116	71	90	64
Model Observations	358	350	844	844	800	580	586	437
R-Squared (Pseudo)	0.251	0.204	0.195	0.202	0.223	0.185	0.159	0.231
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 56a.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Treatment Variable: by Student's Postsecondary Expectations: any Postsecondary Institution Type

Models (Std. Error)	*Post-Match, Weighted Regression* *Student's Postsecondary Expectations* Unsure		Enroll in College		≥ 4-yr degree	
	(1) OLS	(2) Logistic	(3) OLS	(4) Logistic	(5) OLS	(6) Logistic
Past Account Creation + Past Asset Reallocation + Future Intention	-0.108 (0.101)	0.467 (0.302)	0.0510** (0.0225)	1.800** (0.535)	0.0476** (0.0225)	1.767* (0.551)
Sample Size:						
N. Treatment	147	123	1,442	1,442	1,383	1,383
N. Non-Intent (control)	111	106	892	892	844	844
Model Observations	309	276	2,841	2,841	2,714	2,714
R-Squared (Pseudo)	0.323	0.233	0.184	0.239	0.176	0.239
Models conditioned on:						
pscores	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 56b.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Individual Savings Components Nested in Treatment Strategy: by Student's Postsecondary Expectations: any Postsecondary Institution Type

	Post-Match, Weighted Regression					
	Student's Postsecondary Expectations					
Models	Unsure		Enroll in College		≥ 4-yr degree	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Logistic	OLS	Logistic	OLS	Logistic
Saving	-0.0412	0.809	-0.0129	0.885	-0.00522	0.979
	(0.0800)	(0.406)	(0.0177)	(0.194)	(0.0174)	(0.228)
Insurance	-0.0789	0.413*	-0.00900	0.908	-0.0127	0.857
	(0.0693)	(0.210)	(0.0160)	(0.174)	(0.0158)	(0.174)
U.S. Bonds	0.0328	1.550	0.0235	1.314	0.0215	1.304
	(0.0757)	(0.870)	(0.0149)	(0.276)	(0.0147)	(0.298)
Stock/Real Estate	-0.0526	0.708	-0.0246	0.745	-0.0207	0.759
	(0.0740)	(0.367)	(0.0157)	(0.150)	(0.0152)	(0.164)
Other Savings	0.00705	0.998	0.0365**	1.491**	0.0246	1.300
	(0.0788)	(0.502)	(0.0155)	(0.299)	(0.0154)	(0.274)
529 plan	0.0724	2.412	0.00677	1.201	0.00804	1.245
	(0.0816)	(1.400)	(0.0153)	(0.255)	(0.0151)	(0.278)
Add Job	0.0809	1.676	-0.0219	0.714*	-0.0179	0.725
	(0.0696)	(0.767)	(0.0161)	(0.140)	(0.0158)	(0.151)
Reduce Expenses	-0.0216	1.079	-0.00141	1.003	-0.00643	0.928
	(0.0783)	(0.759)	(0.0219)	(0.264)	(0.0211)	(0.259)
Remortgage	0.0471	1.843	-0.0130	0.953	-0.0210	0.823
	(0.0837)	(1.444)	(0.0194)	(0.257)	(0.0194)	(0.238)
Plan to Reduce Expenses	-0.0433	0.567	0.0489*	1.672	0.0446*	1.705
	(0.121)	(0.596)	(0.0272)	(0.546)	(0.0262)	(0.607)
Plan to Remortgage	-0.00868	0.924	0.00911	1.091	0.0108	1.111
	(0.0876)	(0.672)	(0.0175)	(0.246)	(0.0172)	(0.270)
Sample Size:						
N. Savings	119	100	1,132	1,132	1,087	1,087
N. Insurance	59	49	586	586	562	562
N. U.S. Bonds	49	41	539	539	518	518
N. Stock/Real Estate	60	43	767	767	739	739
N. Other Savings	64	52	514	514	493	493
N. 529 plan	35	29	553	553	542	542
N. Add Job	62	52	572	572	550	550
N. Reduce Expenses	117	102	1,238	1,238	1,189	1,189
N. Remortgage	33	26	259	259	249	249
N. Plan to Reduce Exp.	143	122	1,371	1,371	1,317	1,317
N. Plan to Remortgage	35	26	371	371	360	360
Model Observations	309	276	2,841	2,841	2,714	2,714
R-Squared (Pseudo)	0.333	0.252	0.187	0.243	0.177	0.242
Models conditioned on:						
pscores	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.
*** p<0.01, ** p<0.05, * p<0.1

Table 57a.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Treatment Variable: by Postsecondary Institution Type

	Post-Match, Weighted Regression Enrolled Institution Type (Observed)							
Models	2-yr Institution		4-yr Institution		Public, 4-yr Institution		Private, 4-yr Institution	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logit	OLS	Logit	OLS	Logit	OLS	Logit
Past Account Creation + Past Asset Reallocation + Future Intention	0.0203 (0.0316)	1.120 (0.191)	0.00886 (0.0307)	1.020 (0.183)	-0.00357 (0.0334)	0.973 (0.163)	0.0249 (0.0281)	1.186 (0.224)
Sample Size:								
N. Treatment	1,589	1,589	1,589	1,578	1,583	1,572	1,583	1,572
N. Non-Intent (control)	1,003	1,003	1,003	996	1,002	995	1,002	995
Model Observations	3,150	3,150	3,150	3,130	3,139	3,119	3,139	3,119
R-Squared (Pseudo)	0.058	0.053	0.307	0.250	0.135	0.113	0.082	0.084
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Table 57b.

Propensity Score Matching Naïve, Matched, and Post-Match Models for Student Enrollment: Past Account Creation + Past Asset Reallocation + Future Intention: Binary Individual Savings Components Nested in Treatment Strategy: by Postsecondary Institution Type

	Post-Match, Weighted Regression							
	Enrolled Institution Type (Observed)							
Models	2-yr Institution		4-yr Institution		Public, 4-yr Institution		Private, 4-yr Institution	
(Std. Error)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Logit	OLS	Logit	OLS	Logit	OLS	Logit
Saving	0.0249	1.143	-0.0528**	0.733**	0.00196	1.004	-0.0560**	0.679**
	(0.0248)	(0.161)	(0.0239)	(0.108)	(0.0268)	(0.136)	(0.0237)	(0.103)
Insurance	0.00990	1.062	-0.0166	0.913	-0.0116	0.942	-0.00141	1.008
	(0.0223)	(0.129)	(0.0213)	(0.118)	(0.0232)	(0.110)	(0.0192)	(0.137)
U.S. Bonds	0.00996	1.082	0.0149	1.043	0.0261	1.152	-0.0144	0.925
	(0.0222)	(0.134)	(0.0215)	(0.136)	(0.0243)	(0.135)	(0.0202)	(0.128)
Stock/Real Estate	-0.0212	0.890	-0.00418	0.978	-0.0351	0.847	0.0316	1.247
	(0.0226)	(0.112)	(0.0219)	(0.129)	(0.0245)	(0.102)	(0.0207)	(0.178)
Other Savings	0.0435*	1.283**	-0.00588	0.945	-0.0151	0.938	0.00773	1.072
	(0.0229)	(0.158)	(0.0219)	(0.124)	(0.0238)	(0.113)	(0.0203)	(0.151)
529 plan	-0.0415*	0.780*	0.0572***	1.417***	0.0323	1.140	0.0266	1.188
	(0.0222)	(0.100)	(0.0213)	(0.188)	(0.0246)	(0.138)	(0.0208)	(0.163)
Add Job	-0.00367	0.984	-0.00929	0.946	-0.0219	0.909	0.0137	1.105
	(0.0232)	(0.126)	(0.0221)	(0.127)	(0.0244)	(0.111)	(0.0209)	(0.159)
Reduce Expenses	-0.0421	0.785	0.0245	1.162	0.0686**	1.392**	-0.0409	0.749
	(0.0314)	(0.132)	(0.0305)	(0.205)	(0.0327)	(0.235)	(0.0298)	(0.139)
Remortgage	0.0275	1.157	-0.0375	0.786	-0.0684**	0.701**	0.0301	1.195
	(0.0285)	(0.183)	(0.0275)	(0.133)	(0.0307)	(0.108)	(0.0279)	(0.204)
Plan to Reduce Expenses	0.0323	1.194	0.0155	1.086	-0.0404	0.817	0.0583	1.464
	(0.0401)	(0.273)	(0.0394)	(0.255)	(0.0440)	(0.178)	(0.0389)	(0.377)
Plan to Remortgage	-0.00458	0.977	0.0251	1.133	0.00307	1.007	0.0222	1.159
	(0.0261)	(0.142)	(0.0255)	(0.176)	(0.0280)	(0.140)	(0.0241)	(0.182)
Sample Size:								
N. Savings	1,251	1,251	1,251	1,243	1,247	1,239	1,247	1,239
N. Insurance	645	645	645	640	642	637	642	637
N. U.S. Bonds	588	588	588	586	586	584	586	584
N. Stock/Real Estate	827	827	827	820	824	817	824	817
N. Other Savings	578	578	578	573	575	570	575	570
N. 529 plan	588	588	588	581	586	579	586	579
N. Add Job	634	634	634	629	630	625	630	625
N. Reduce Expenses	1,355	1,355	1,355	1,346	1,351	1,342	1,351	1,342
N. Remortgage	292	292	292	289	291	288	291	288
N. Plan to Reduce Exp.	1,514	1,514	1,514	1,503	1,509	1,498	1,509	1,498
N. Plan to Remortgage	406	406	406	404	404	402	404	402
Model Observations	3,150	3,150	3,150	3,130	3,139	3,119	3,139	3,119
R-Squared (Pseudo)	0.062	0.057	0.310	0.254	0.140	0.117	0.088	0.090
Models conditioned on:								
pscores	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Saved & GPA	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses. Logistic models report pseudo R-Squared. The models (numerically identified) include all of the individual savings variables. The individual variables are binary coded Yes= 1 if a household has included that option in its savings portfolio and No=0 if they have not included it. Observations are dropped from Logistic models when they predict failure perfectly, accounting for sample size differences between OLS and Logistic models.

*** p<0.01, ** p<0.05, * p<0.1

Appendix B – Figures

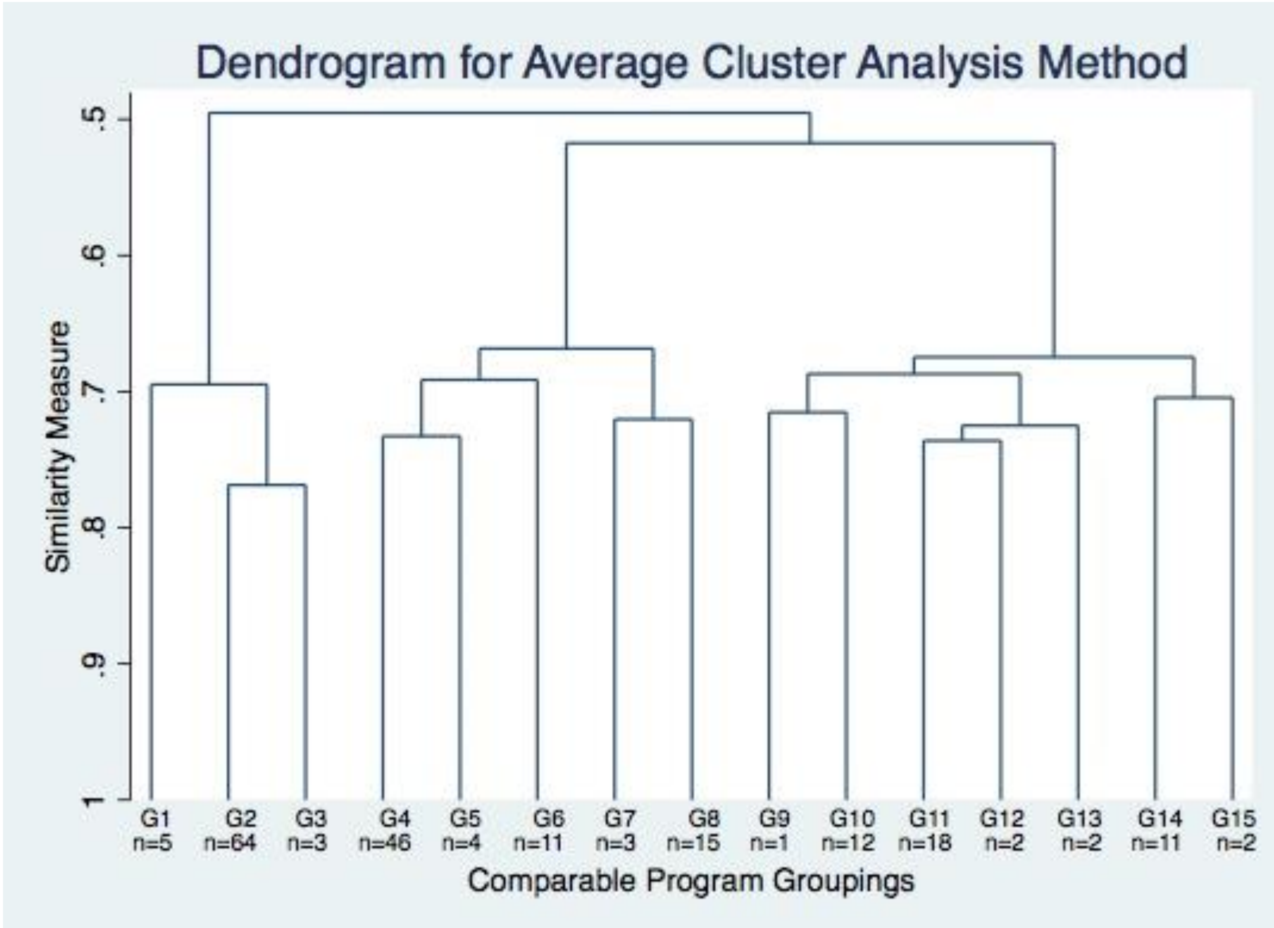

Figure 1. Cluster Analysis Dendrogram Tree for Average linkage with matching coefficients Method: Sample Population of Residency-Based Aid Programs. G1-G15 represents the numbering for the order groups were created. The number of programs within each group is listed below the group number. Dendrogram trees illustrate the net difference in similarity calculations at the point when groups are merged. The Dendrogram trees can be used to discern when groups of non-similar programs were combined to achieve the single cluster. Vertical "branches" represent the net difference in the similarity calculations.

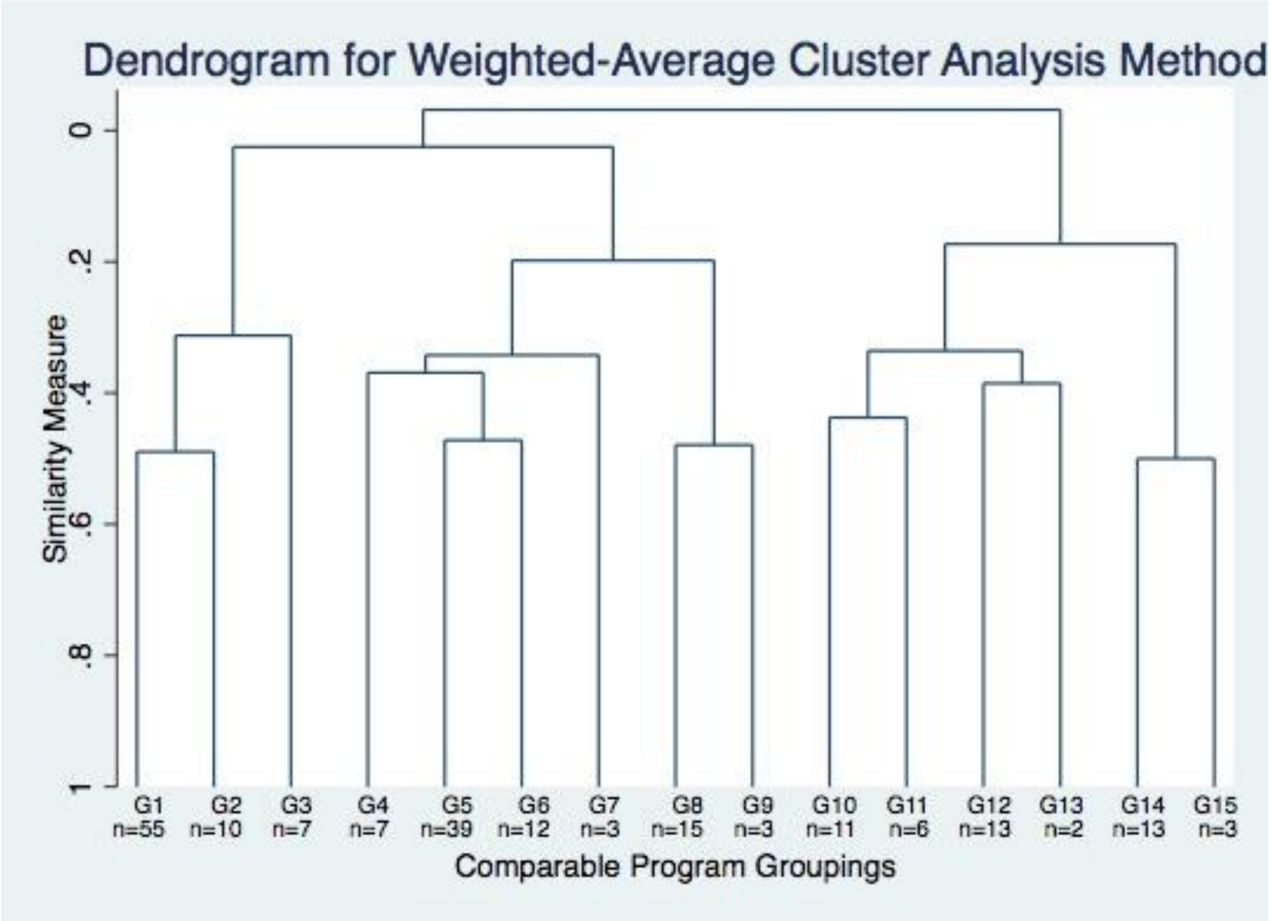

Figure 2. Cluster Analysis Dendrogram Tree for Weighted Average linkage Method: Sample Population of Residency-Based Aid Programs. G1-G15 represents the numbering for the order groups were created. The number of programs within each group is listed below the group number. Dendrogram trees illustrate the net difference in similarity calculations at the point when groups are merged. The Dendrogram trees can be used to discern when groups of non-similar programs were combined to achieve the single cluster. Vertical "branches" represent the net difference in the similarity calculations.

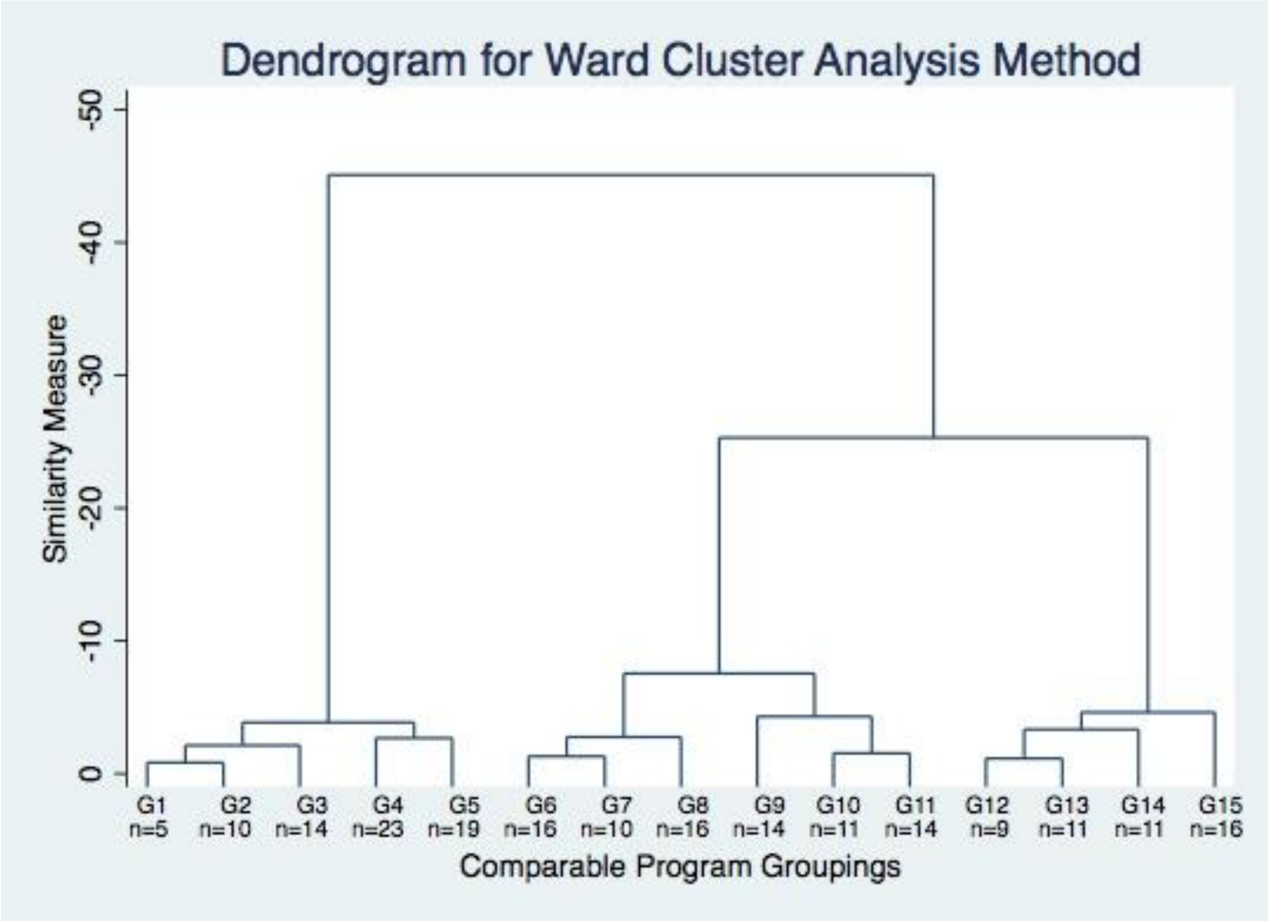

Figure 3. Cluster Analysis Dendrogram Tree for Ward linkage Method: Sample Population of Residency-Based Aid Program. G1-G15 represents the numbering for the order groups were created. The number of programs within each group is listed below the group number. Dendrogram trees illustrate the net difference in similarity calculations at the point when groups are merged. The Dendrogram trees can be used to discern when groups of non-similar programs were combined to achieve the single cluster. Vertical “branches” represent the net difference in the similarity calculations.

Kindergarten through Junior High	High School	No Commitment
Nicolet Promise		
13th Year Promise		
SLCC Promise		
tnAchieves (Knox Achieves)		
Educate and Grow		
Ayers Foundation Scholars Program		
Morgan Success		
CORE Promise		
50th Anniversary Scholars		
VanGuarantee		
Pontiac Promise		
Northport Promise		
Muskegon Promise		
Legacy Scholars		
Kalamazoo Promise		
Hazel Park Promise		
Detroit Scholarship Fund		
Benton Harbor Promise		
Garrett County Scholarship Program		
Louisville Rotary	Dyer County Promise Scholarship	
Hopkinsville Rotary Scholars	Pittsburgh Promise	
College Bound Scholarship	Tulsa Achieves	
Peoria Promise	Say Yes to Education: Syracuse	Shoreline Scholars
Galesburg Promise	Say Yes to Education: Buffalo	Beacon of Hope
Dell and Evelyn Carroll Scholarship	School Counts!:Cumberland	Rusk TJC Citizens Promise
Chicago Star Scholarship	School Counts!:Carney's	Philadelphia Education Fund
American Dream Scholarship	Missouri A+ Scholarship	Future Connect
New Haven Promise	Saginaw Promise	Bernard Daly Educational Fund
Aims Comm. Coll. Promise	Lansing Promise	Montgomery Cnty Ohio
West Valley College Community Grant	Detroit College Promise	Champion City Scholars Program
Ventura College Promise	Baldwin Promise	Newark College Promise
Valley-Bound Commitment	School Counts!:Madisonville	Cooperman College Scholarship
Siskiyous Promise	Community Scholarship Program	Power of YOU
SBCC Promise	Harper College Promise	Jackson Legacy
Long Beach College Promise	Rosen Foundation Scholarship	Bay Commitment Scholarship
The Cuesta Promise	Denver Scholarship Foundation	Rockford Promise
Adelante Promise	Oakland Promise	Buffalo Scholarship Foundation
Promise of the Future	School Counts!: Morrilton	DCTAG
El Dorado Promise	Great River Promise - Phillips	Youth 2 Leaders Education Foundation
Arkadelphia Promise	Great River Promise Scholarship	The Fulfillment Fund

Figure 4. Timeframe: Identifying the earliest point in time students begin to satisfy the residency longevity requirement to earn the financial aid commitment. Programs that do not have a longevity requirement are categorized as Kindergarten through Junior High. Categories are mutually exclusive.

			Nicolet Promise
			Shoreline Scholars
			13th Year Promise
			SLCC Promise
			tnAchieves (Knox Achieves)
			Educate and Grow
			Pittsburgh Promise
			Morgan Success
			50th Anniversary Scholars
			Bernard Daly Educational Fund
			Tulsa Achieves
			Montgomery Cnty Ohio
			Champion City Scholars Program
			Say Yes to Education: Syracuse
			Say Yes to Education: Buffalo
			School Counts!:Cumberland
			School Counts!:Carney's
			Cooperman College Scholarship
			VanGuarantee
			Missouri A+ Scholarship
			Power of YOU
			Muskegon Promise
			Detroit Scholarship Fund
			Garrett County Scholarship
			Louisville Rotary
			Hopkinsville Rotary Scholars
			Community Scholarship Program
			Harper College Promise
			Carroll Scholarship
			Chicago Star Scholarship
			Rosen Foundation
Dyer County Promise			American Dream
CORE Promise			Aims Comm. Coll. Promise
Future Connect	Beacon of Hope		Youth 2 Leaders
Saginaw Promise	Rusk TJC Citizens Promise		West Valley Community
Northport Promise	Ayers Foundation Scholars		Ventura College Promise
Lansing Promise	Philadelphia Education Fund		Valley-Bound Commitment
Jackson Legacy	Newark College Promise	Legacy Scholars	Siskiyous Promise
Hazel Park Promise	Pontiac Promise	Kalamazoo Promise	SBCC Promise
Detroit College Promise	Baldwin Promise	Benton Harbor Promise	Long Beach College Promise
Bay Commitment Scholarship	Buffalo Scholarship	College Bound Scholarship	The Cuesta Promise
School Counts!:Madisonville	DCTAG	Peoria Promise	Adelante Promise
Rockford Promise	Denver Scholarship	Galesburg Promise	Promise of the Future
New Haven Promise	Oakland Promise	El Dorado Promise	Great River Promise - Phillips
School Counts!: Morrilton	The Fulfillment Fund	Arkadelphia Promise	Great River Promise
Flat or Capped, < $3,000	Flat or Capped, ≥ $3,000	Percent (%)	Unmet Need (Last-Dollar)

Figure 5. Value: Identifies the measurement and maximum value the aid may represent. Single, Flat aid values are separated by value above and below $3,000. Percent references programs that use a longevity equation to determine aid award. Unmet Need is Last-Dollar funding applied to cover remaining expenses after all other non-repayable aid awards are applied. Categories are mutually exclusive.

No Sub-Qualifications	GPA Requirement	Need Requirement	Merit and Need Requirement
13th Year Promise			
tnAchieves (Knox Achieves)			
Educate and Grow			
Dyer County Promise			
Ayers Foundation Scholars			
Morgan Success			
CORE Promise			
Future Connect			
Bernard Daly Educational Fund			
Saginaw Promise			
Pontiac Promise			
Northport Promise			
Legacy Scholars			
Lansing Promise			
Kalamazoo Promise			
Hazel Park Promise			
Detroit Scholarship Fund			
Detroit College Promise	Beacon of Hope		
Benton Harbor Promise	Rusk TJC Citizens Promise		
Bay Commitment Scholarship	Pittsburgh Promise		
Baldwin Promise	Tulsa Achieves		
Garrett County Scholarship	School Counts!:Cumberland		
Rockford Promise	School Counts!:Carney's		
Peoria Promise	Cooperman College Scholarship		
Galesburg Promise	Missouri A+ Scholarship		
Carroll Scholarship	Muskegon Promise		
Rosen Foundation	Jackson Legacy		
Buffalo Scholarship	School Counts!:Madisonville		
DCTAG	Louisville Rotary		
Youth 2 Leaders	Hopkinsville Rotary Scholars		
West Valley College	Community Scholarship Program		
Ventura College Promise	College Bound Scholarship		Nicolet Promise
Siskiyous Promise	Harper College Promise		Shoreline Scholars
SBCC Promise	Chicago Star Scholarship	SLCC Promise	50th Anniversary Scholars
Long Beach College Promise	American Dream	Philadelphia Education Fund	Champion City Scholars
The Cuesta Promise	New Haven Promise	Montgomery Cnty Ohio	Newark College Promise
Adelante Promise	Aims Comm. Coll. Promise	Say Yes to Education: Syracuse	VanGuarantee
Great River Promise - Phillips	The Fulfillment Fund	Say Yes to Education: Buffalo	Denver Scholarship
Great River Promise	Promise of the Future	Power of YOU	Oakland Promise
El Dorado Promise	School Counts!: Morrilton	Valley-Bound Commitment	Arkadelphia Promise

Figure 6. Sub-Qualifications: Identifying additional stipulations that students must meet for eligibility. A program is classified as No Sub-Qualifications if students are not required to meet any benchmarks not related to residency. GPA Requirements refer to secondary school grades or test scores. Need Requirement references whether students must qualify for federal need-based financial aid programs through the FAFSA application process. Merit and Need Requirements identify programs that require both academic and financial stipulations. Categories are mutually exclusive.

< 2.5 GPA	2.5 ≤ GPA < 3.0	≥ 3.0 GPA
	Beacon of Hope	
	Rusk TJC Citizens Promise	
	Pittsburgh Promise	
	Cooperman College Scholarship	
Nicolet Promise	VanGuarantee	
Tulsa Achieves	Missouri A+ Scholarship	
Champion City Scholars	Jackson Legacy	Shoreline Scholars
School Counts!:Cumberland	School Counts!:Madisonville	50th Anniversary Scholars
School Counts!:Carney's	Louisville Rotary	Muskegon Promise
Newark College Promise	Hopkinsville Rotary Scholars	College Bound Scholarship
Harper College Promise	Community Scholarship Program	Chicago Star Scholarship
Denver Scholarship	Denver Scholarship	American Dream
Aims Comm. Coll. Promise	The Fulfillment Fund	New Haven Promise
Oakland Promise	Promise of the Future	Oakland Promise
School Counts!: Morrilton	Arkadelphia Promise	Arkadelphia Promise

Figure 7. Grade Point Average Sub-Qualifications: Identifies the minimum secondary school Grade Point Average required for eligibility. Programs that have multiple GPA benchmarks to determine different award values are listed in multiple categories. Grade Point Average Sub-Qualification spectrum only includes programs with minimum GPA requirement.

Single, Specific Instituion	Select 2- or 4-year	In-State 2-year	In-State 2- & 4-year	Any 2- & 4-year
Nicolet Promise				
Shoreline Scholars				
13th Year Promise				
SLCC Promise				
Rusk TJC Citizens Promise				
Educate and Grow				
Morgan Success				
50th Anniversary Scholars				
Future Connect				
Tulsa Achieves				
Montgomery Cnty Ohio				
Champion City Scholars				
School Counts!:Cumberland				
School Counts!:Carney's				
VanGuarantee				
Legacy Scholars				
Garrett County Scholarship				
School Counts!:Madisonville				
Louisville Rotary				
Hopkinsville Rotary Scholars	tnAchieves (Knox Achieves)			
Community Scholarship Program	Dyer County Promise			
Peoria Promise	CORE Promise			
Harper College Promise	Bernard Daly Educational Fund			
Galesburg Promise	Say Yes to Education: Syracuse			
Carroll Scholarship	Say Yes to Education: Buffalo			
American Dream	Newark College Promise		Beacon of Hope	
Aims Comm. Coll. Promise	Cooperman College Scholarship		Pittsburgh Promise	
West Valley College	Power of YOU		Saginaw Promise	Ayers Foundation Scholars
Ventura College Promise	Muskegon Promise		Pontiac Promise	Philadelphia Education Fund
Valley-Bound Commitment	Lansing Promise		Northport Promise	College Bound Scholarship
Siskiyous Promise	Jackson Legacy		Kalamazoo Promise	Rockford Promise
SBCC Promise	Detroit Scholarship Fund		Hazel Park Promise	DCTAG
Long Beach College Promise	Bay Commitment Scholarship		Detroit College Promise	Youth 2 Leaders
The Cuesta Promise	Chicago Star Scholarship		Baldwin Promise	Oakland Promise
Adelante Promise	Buffalo Scholarship		Rosen Foundation	The Fulfillment Fund
School Counts!: Morrilton	Promise of the Future	Missouri A+ Scholarship	New Haven Promise	El Dorado Promise
Great River Promise	Great River Promise - Phillips	Benton Harbor Promise	Denver Scholarship	Arkadelphia Promise

Figure 8. Institutional Type: Identifies what type of institution or set of institutions that aid may be redeemed. Categories are mutually exclusive. Programs aligned with a specific institution are classified as Single, Specific. Programs that can be redeemed at a list of select institutions are classified as Select 2- or 4-year. Programs that can be redeemed at all two-year institutions within the state are categorized as In-State 2-year. Programs that all aid to be redeemed at all in-state institutions are classified as In-State 2- & 4-year. Programs that allow aid to be used outside of the state are classified as Any 2-& 4-year.

		Detroit College Promise	
		Bay Commitment Scholarship	Nicolet Promise
		Garrett County Scholarship	Shoreline Scholars
		School Counts!:Madisonville	13th Year Promise
		Louisville Rotary	Beacon of Hope
		Community Scholarship Program	SLCC Promise
		College Bound Scholarship	Rusk TJC Citizens Promise
		Rockford Promise	tnAchieves (Knox Achieves)
		Peoria Promise	Educate and Grow
		Harper College Promise	Dyer County Promise
		Galesburg Promise	Ayers Foundation Scholars
		Carroll Scholarship	Pittsburgh Promise
		Chicago Star Scholarship	Philadelphia Education Fund
		Rosen Foundation	Morgan Success
		Buffalo Scholarship	CORE Promise
		American Dream	50th Anniversary Scholars
		DCTAG	Future Connect
		New Haven Promise	Bernard Daly Educational Fund
		Aims Comm. Coll. Promise	Tulsa Achieves
		Ventura College Promise	Montgomery Cnty Ohio
		Siskiyous Promise	Missouri A+ Scholarship
	Say Yes to Education: Syracuse	SBCC Promise	Power of YOU
	Say Yes to Education: Buffalo	The Fulfillment Fund	Saginaw Promise
	Detroit Scholarship Fund	The Cuesta Promise	Pontiac Promise
Champion City Scholars	Hopkinsville Rotary Scholars	Promise of the Future	Northport Promise
Legacy Scholars	Denver Scholarship	School Counts!: Morrilton	Muskegon Promise
Benton Harbor Promise	West Valley College	Great River Promise - Phillips	Lansing Promise
Baldwin Promise	Valley-Bound Commitment	Great River Promise	Kalamazoo Promise
Youth 2 Leaders	Oakland Promise	El Dorado Promise	Jackson Legacy
Long Beach College Promise	Adelante Promise	Arkadelphia Promise	Hazel Park Promise
Yes, pre- High School	Yes, High School	No Program	

Figure 9. Supporting Programs: Identifies if a program includes access to mentoring, college readiness programs, or a network of advisors to guide students through the process of transitioning into higher education. Programs that do include a non-monetary support program are categorized based on when students may begin to access the network: prior to secondary school (pre- 9th grade) or during secondary school years (9th-12th grade). Categories are mutually exclusive.

<table>
<tr><th></th><th>< $3,000 aid award</th><th>≥ $3,000 aid award</th><th>Percent (%)</th><th colspan="2">Unmet Need (Last Dollar)</th></tr>
<tr><td>Kindergarten through 8th</td><td>New Haven Promise
Hazel Park Promise
Northport Promise
CORE Promise</td><td>Pontiac Promise
Ayers Foundation</td><td>Arkadelphia Promise
El Dorado Promise
Galesburg Promise
Peoria Promise
College Bound Scholar.
Benton Harbor Promise
Kalamazoo Promise
Legacy Scholars</td><td>Promise of the Future
Adelante Promise
Cuesta Promise
Long Beach College
SBCC Promise
Siskiyous Promise
Valley-Bound Commit.
Ventura College Promise
West Valley Community
Aims C.C. Promise
American Dream
Carroll Scholarship
Chicago Star Scholarship</td><td>Hopkinsville Rotary
Louisville Rotary
Garrett County
Detroit Scholarship Fund
Muskegon Promise
VanGuarantee
50th Anniversary
Morgan Success
Educate and Grow
tnAchieves
SLCC Promise
13th Year Promise
Nicolet Promise</td></tr>
<tr><td>9th through 12th grade</td><td>Counts!: Morrilton
Counts!: Madisonville
Detroit College Promise
Lansing Promise
Saginaw Promise
Dyer County Promise</td><td>Oakland Promise
Denver Scholarship
Baldwin Promise</td><td></td><td>Great River Promise
Great River - Phillips
Rosen Foundation
Harper College Promise
Missouri A+
Community Scholarship</td><td>Counts!: Carney's
Counts!: Cumberland
Say Yes: Buffalo
Say Yes: Syracuse
Tulsa Achieves
Pittsburgh Promise</td></tr>
<tr><td>No Commitment</td><td>Rockford Promise
Bay Commitment
Jackson Legacy
Future Connect</td><td>Fulfillment Fund
DCTAG
Buffalo Scholarship
Newark College Promise
Philadelphia Education
Rusk TJC Citizens
Beacon of Hope</td><td></td><td colspan="2">Youth 2 Leaders
Power of YOU
Cooperman College
Montgomery County Ohio
Champion City Scholars
Bernard Daly Educational
Shoreline Scholars</td></tr>
</table>

Figure 10. Two-Dimension Spectrum overlay for *Timeframe* and *Value*. Community-Sustained program names are abbreviated to conserve space. Program alignment is based on categorization in each of the two spectrums. Categories are mutually exclusive.

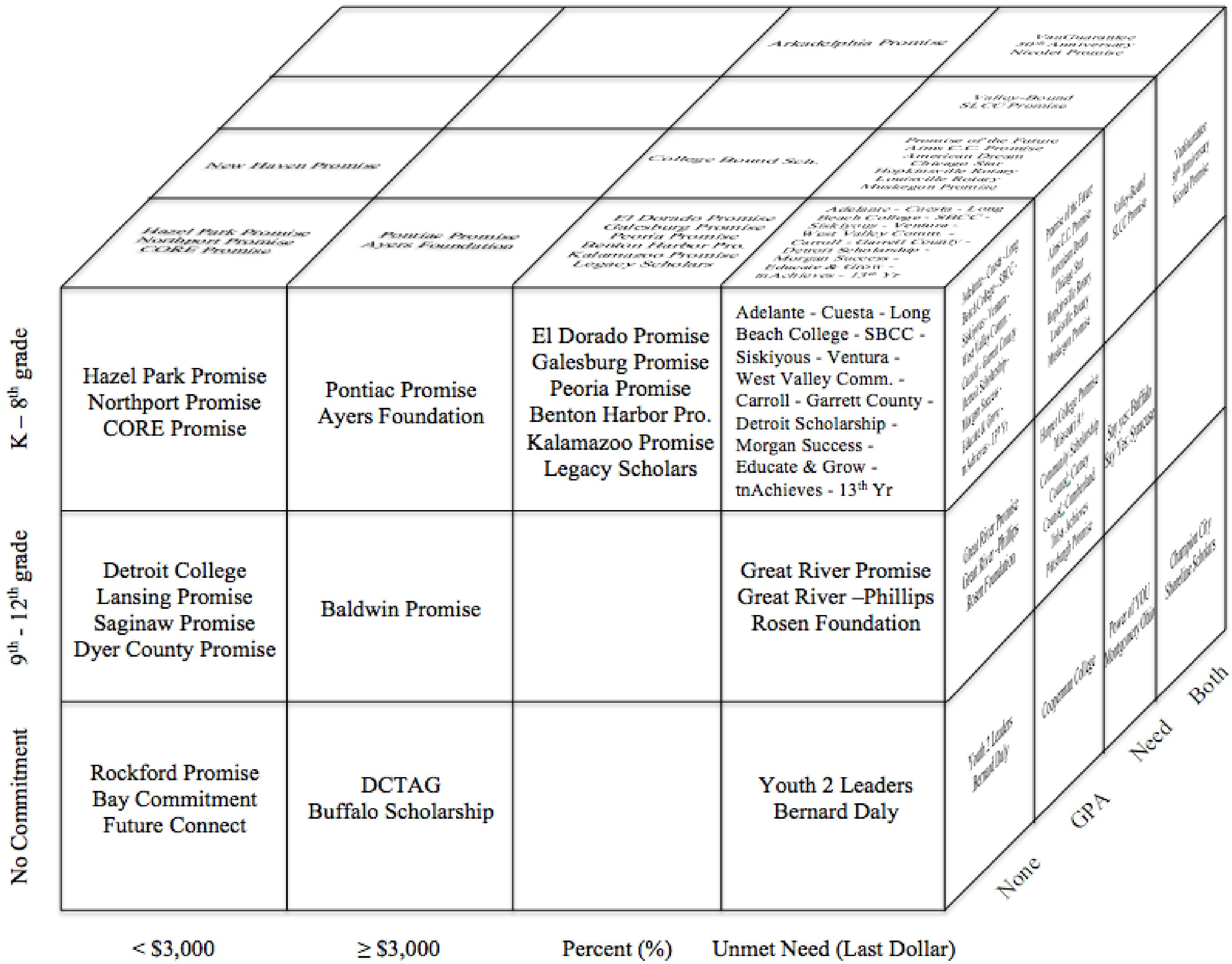

Figure 11. Three-Dimensional Cube of *Timeframe*, *Value*, and *Sub-Qualifications* spectrum. Community- Sustained program names are abbreviated to conserve space.

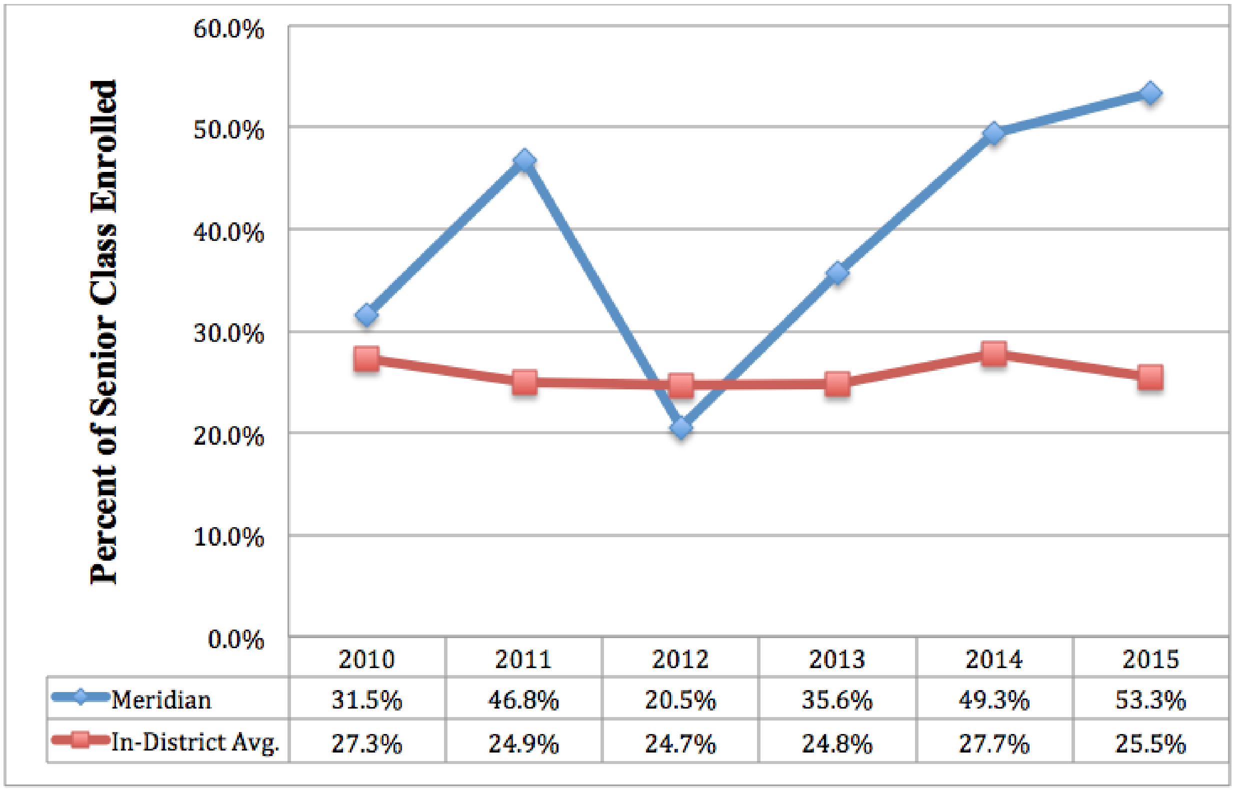

Figure 12. Yearly Richland enrollment trends, by high school graduating Senior Class, by In-District and Carroll Scholarship eligible Meridian High School. Percentages are based on the number of students with postsecondary academic records at Richland and the high schools reported number of graduates for each senior class. In-District averages are the combination of the 13 Non-Meridian In-District high schools.

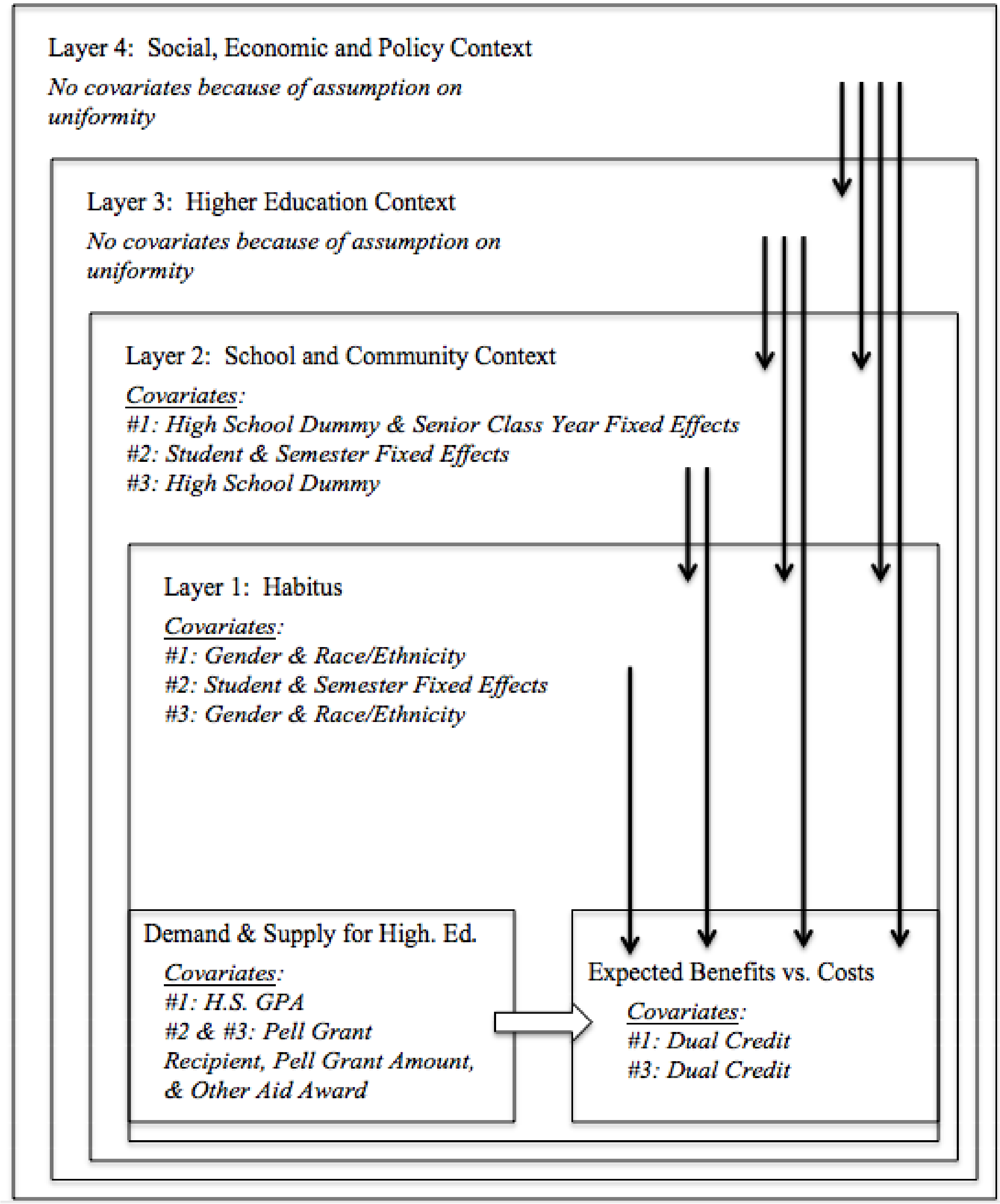

Figure 13. Adaption of Perna's Conceptual Framework and DID Model Covariates Identified by Research Question Number

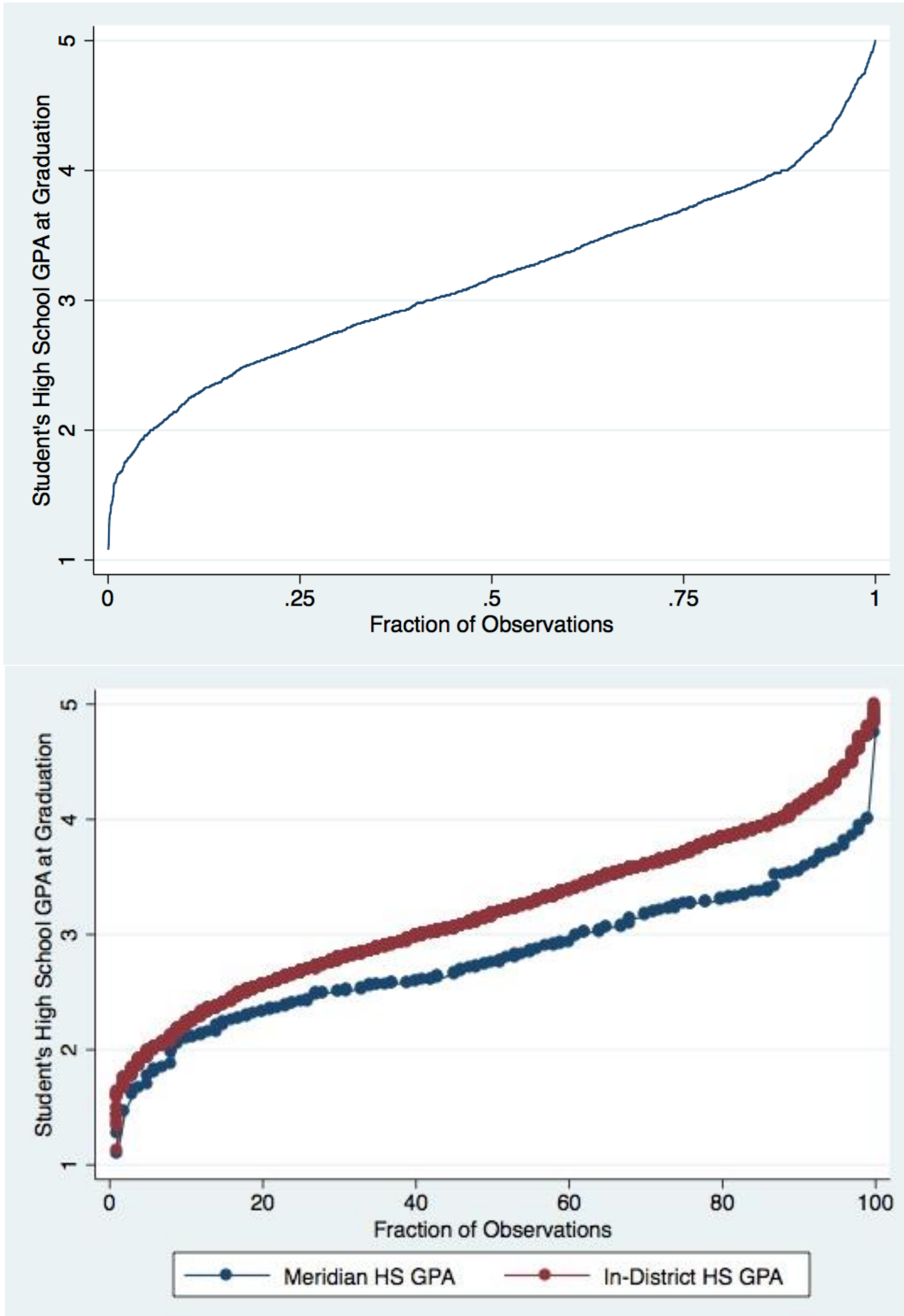

Figure 14. Quantile distribution of High School Grade Point Averages for Students that Enrolled at Richland; the full sample and separated by Meridian and In-District high schools. The vertical axis measures the range of *HS GPA* and the horizontal axis measures the percentage of the population. The area under the curve signifies the percentage of the population with the specific *HS GPA* value or below.

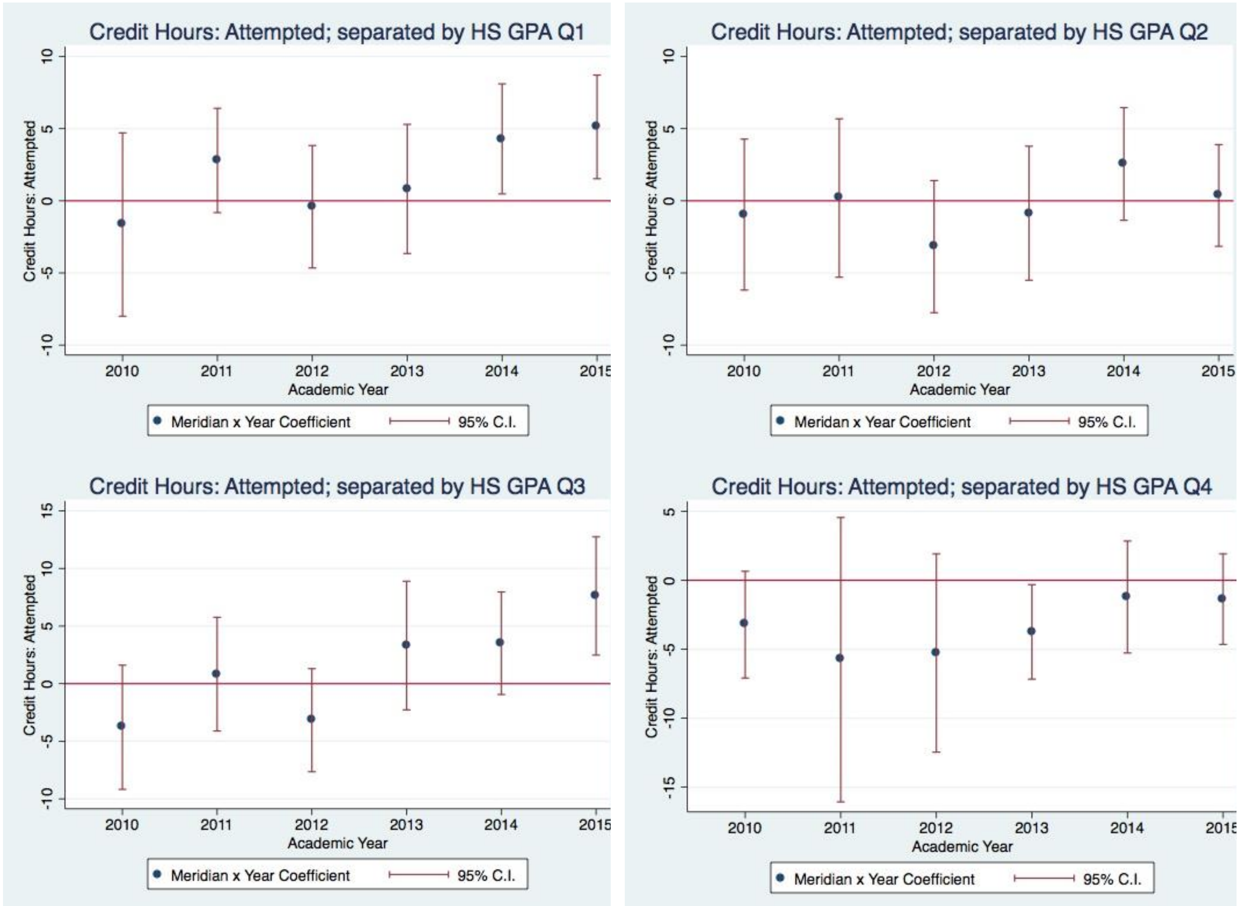

Figure 15. Graph of prior year trends for *Credit Hours: Attempted* in an academic year, separated by *HS GPA* quartile. The horizontal line represents a zero coefficient value. For years when the 95% confidence interval bars overlap the zero coefficient value, I reject the null hypothesis that there is a difference in mean values for treatment school and the control schools. The Carroll Scholarship began in academic year 2013. All years 2013 and after represent when students had information on the award.

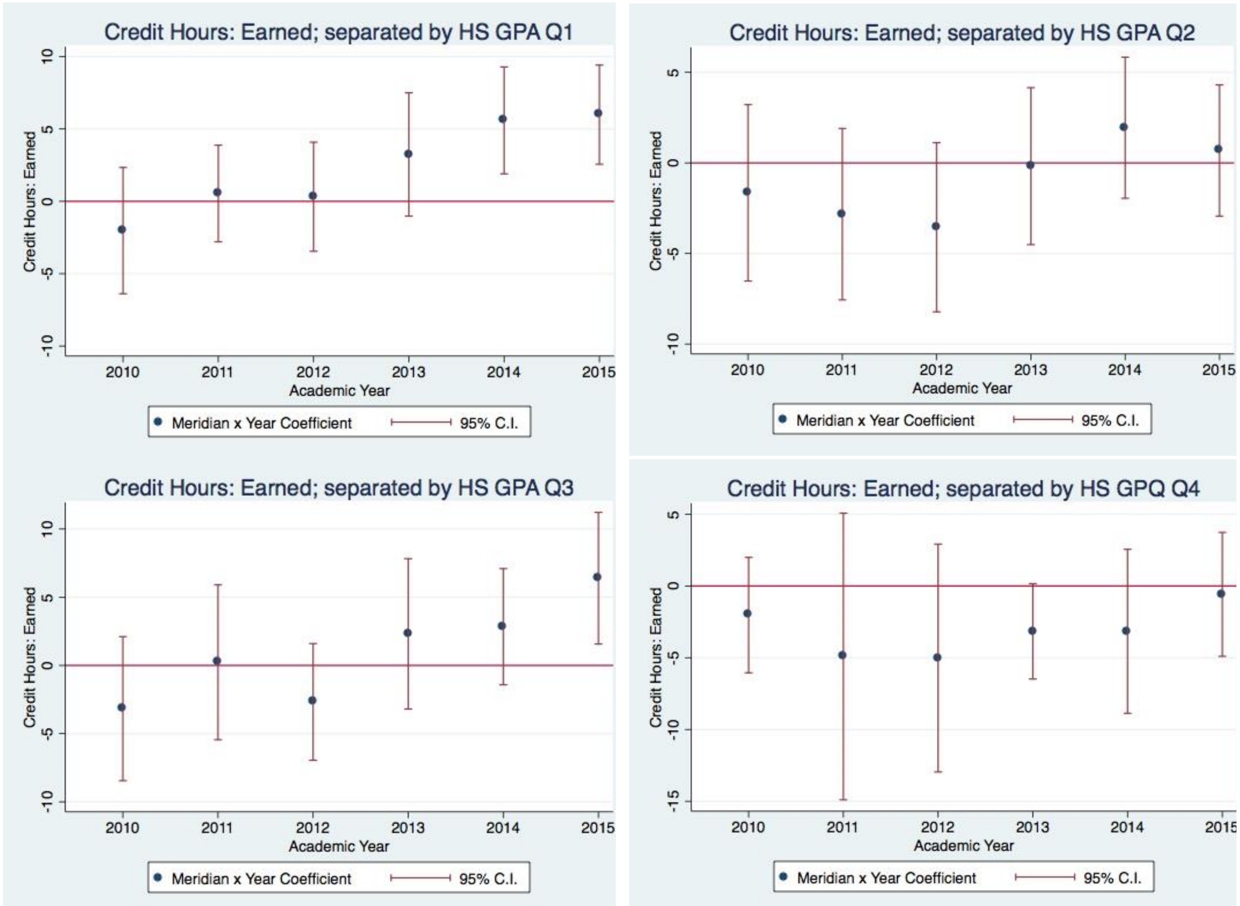

Figure 16. Graph of prior year trends for *Credit Hours: Earned* in an academic year, separated by *HS GPA* quartile. The horizontal line represents a zero coefficient value. For years when the 95% confidence interval bars overlap the zero coefficient value, I reject the null hypothesis that there is a difference in mean values for treatment school and the control schools. The Carroll Scholarship began in academic year 2013. All years 2013 and after represent when students had information on the award.

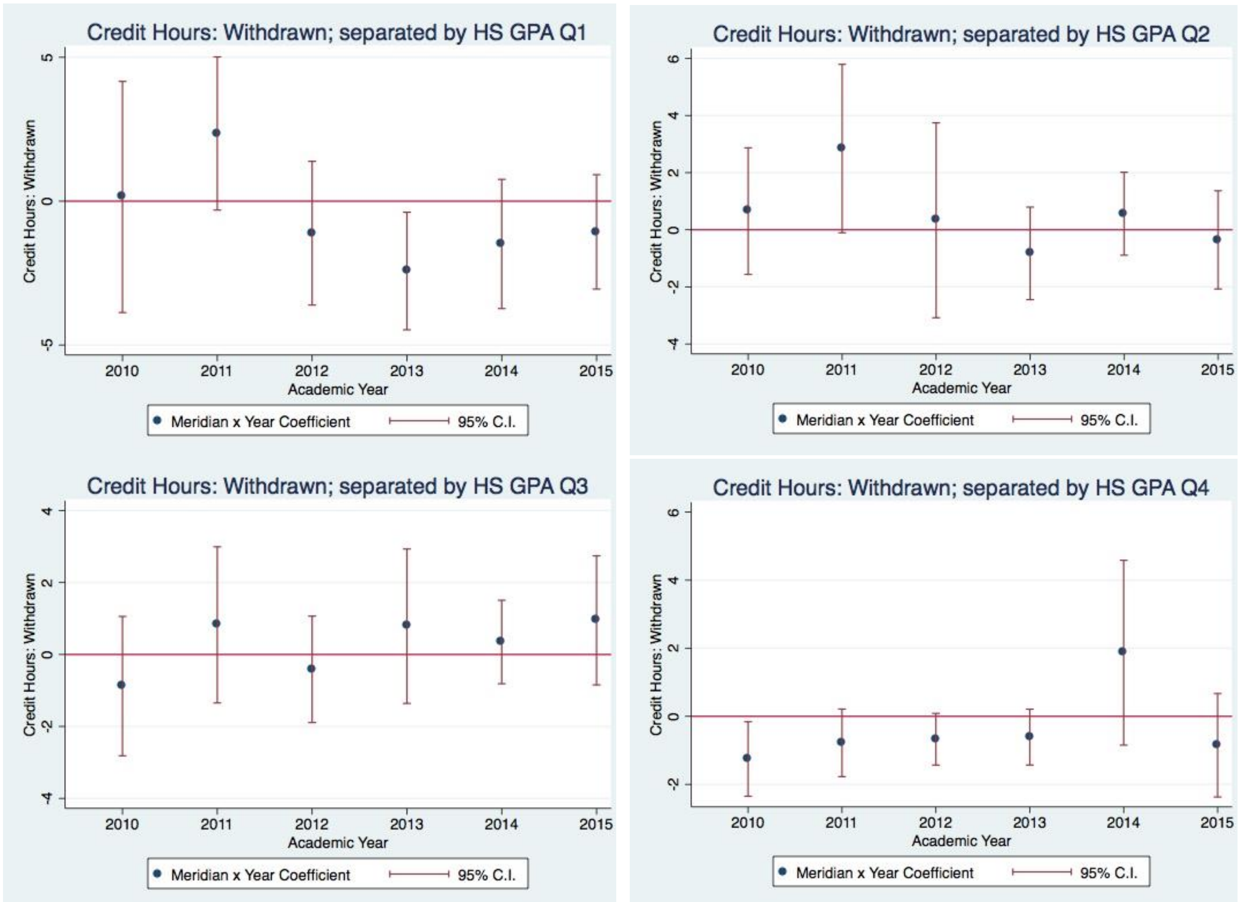

Figure 17. Graph of prior year trends for *Credit Hours: Withdrawn* in an academic year, separated by *HS GPA* quartile. The horizontal line represents a zero coefficient value. For years when the 95% confidence interval bars overlap the zero coefficient value, I reject the null hypothesis that there is a difference in mean values for treatment school and the control schools. The Carroll Scholarship began in academic year 2013. All years 2013 and after represent when students had information on the award.

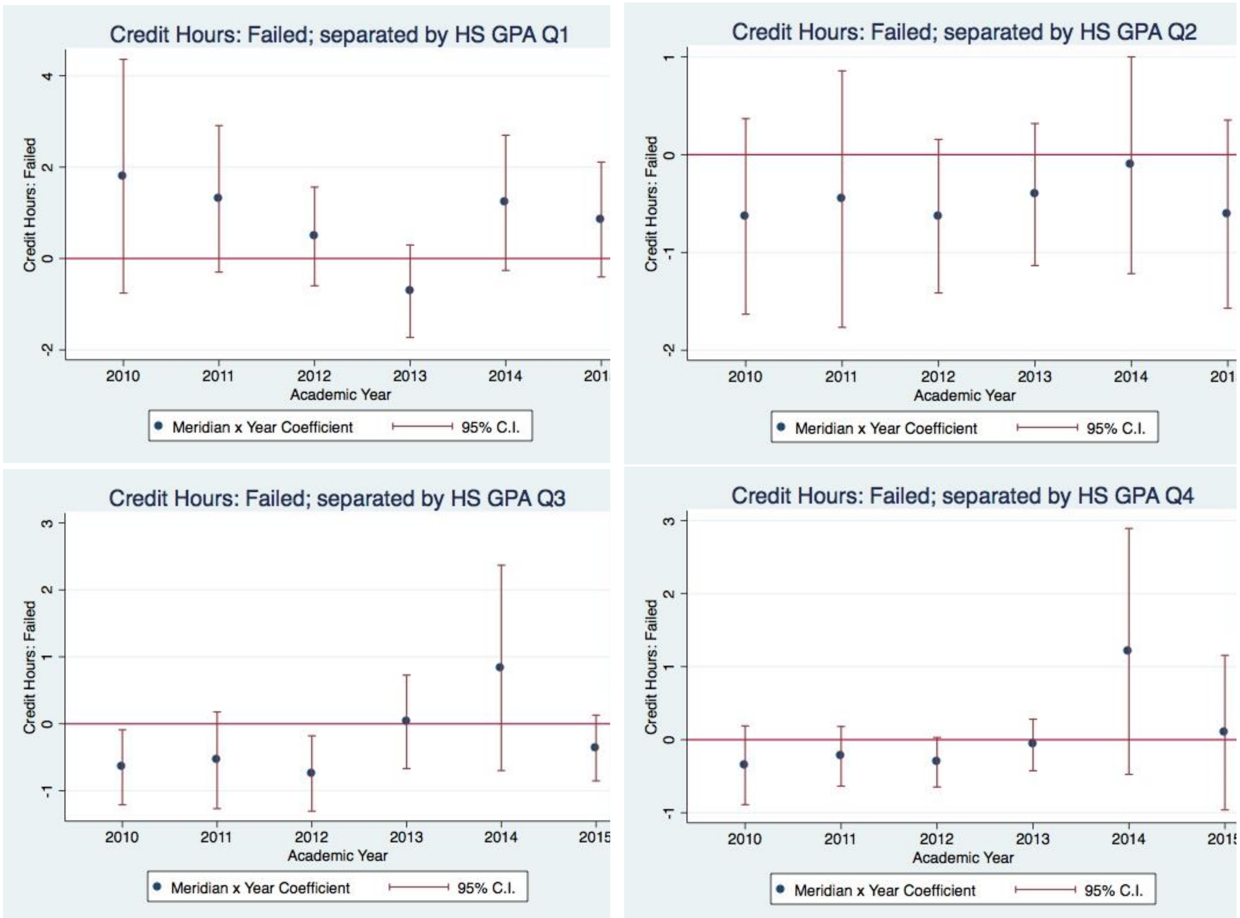

Figure 18. Graph of prior year trends for *Credit Hours: Failed* in an academic year, separated by *HS GPA* quartile. The horizontal line represents a zero coefficient value. For years when the 95% confidence interval bars overlap the zero coefficient value, I reject the null hypothesis that there is a difference in mean values for treatment school and the control schools. The Carroll Scholarship began in academic year 2013. All years 2013 and after represent when students had information on the award.

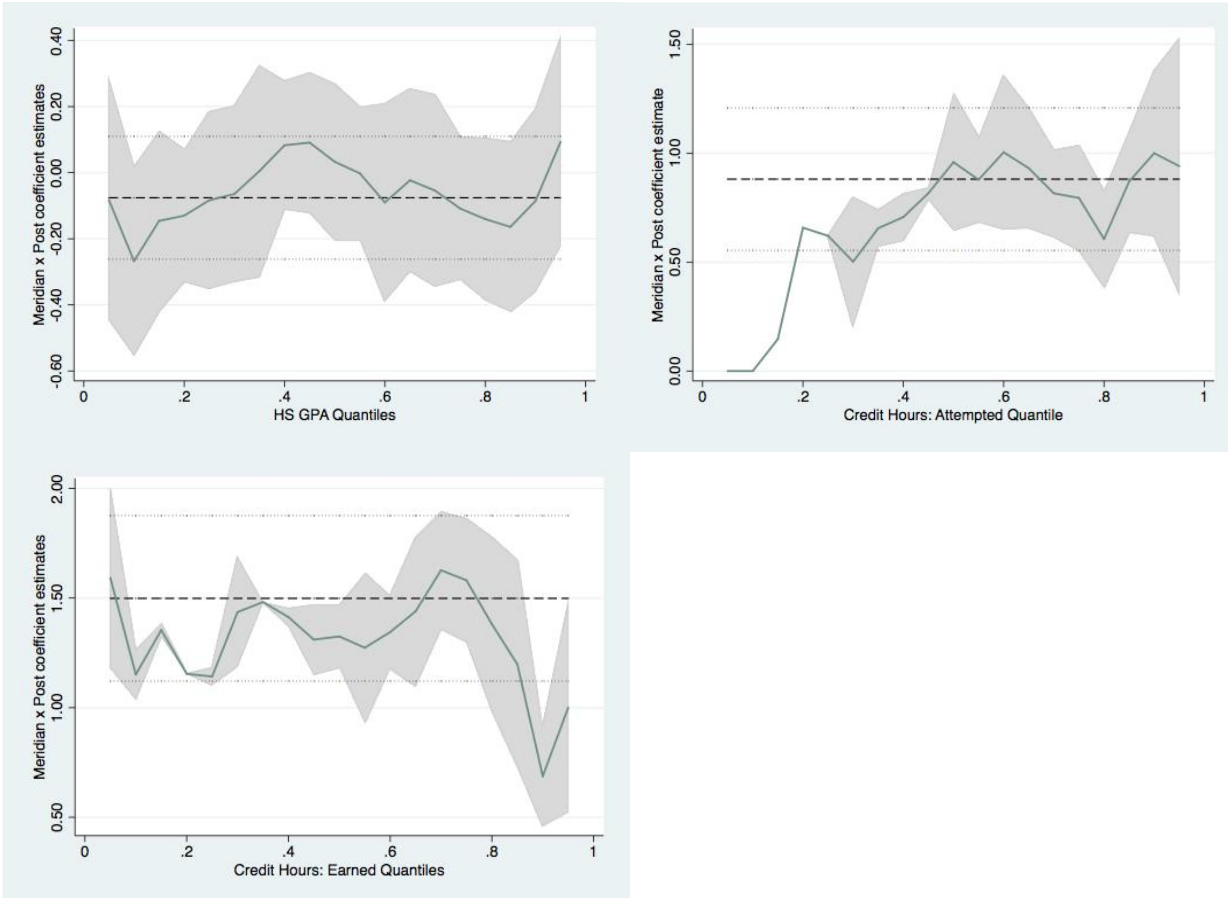

Figure 19. Quantile Regression Coefficient graphs for *HS GPA*, *Credit Hours: Attempted*, and *Credit Hours: Earned*. The horizontal line represents the OLS coefficient value over the full sample. The line of interest represents the coefficient estimate at the corresponding quantile. Quantiles are measured along the bottom axis. For years when the 95% confidence interval (indicated by the grey area in the Figures) overlaps the OLS coefficient value, I reject the null hypothesis that there is a difference in coefficient values between OLS and quantile regression.

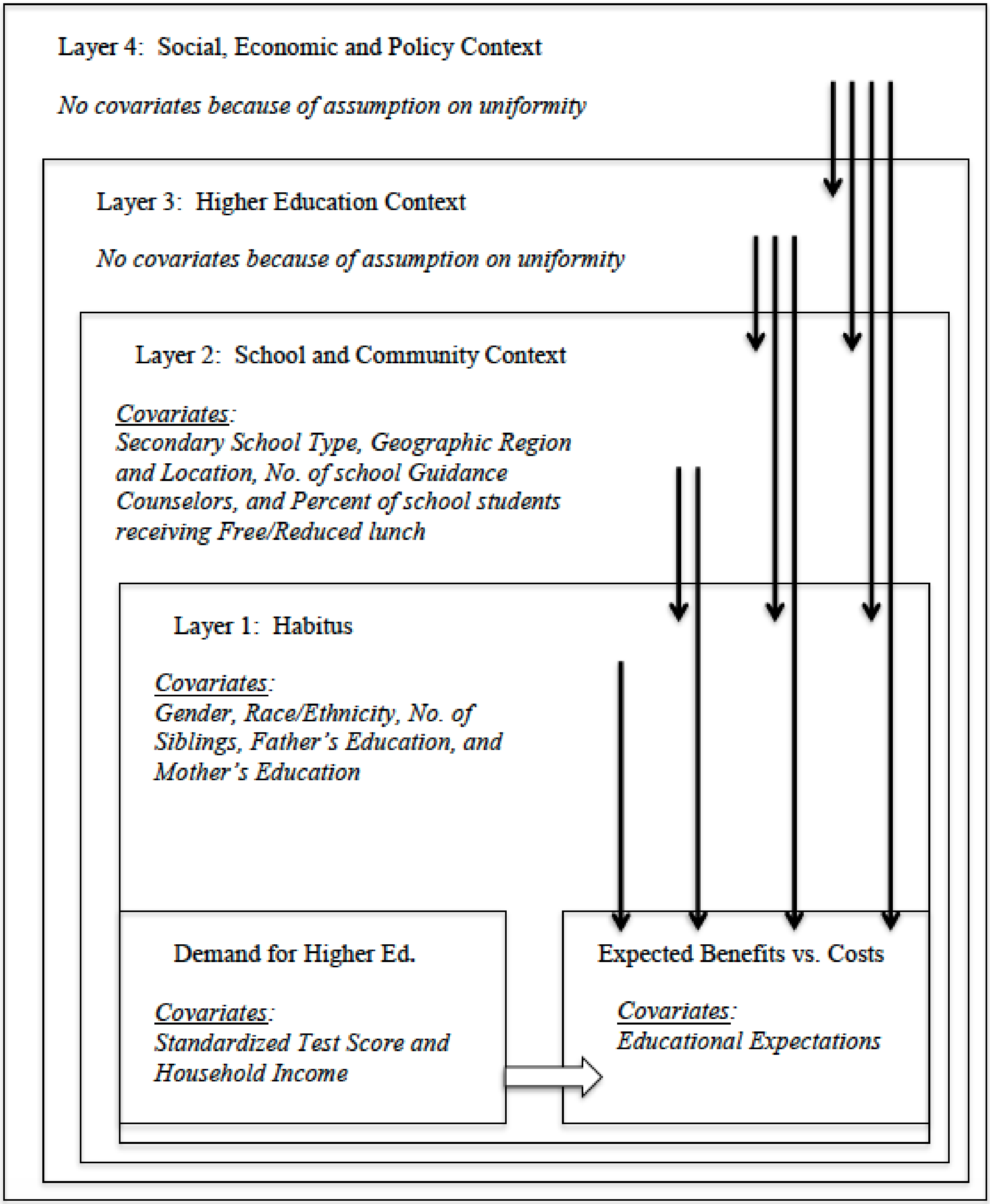

Figure 20. Adaptation of Perna's Conceptual Framework and PSM Estimator covariates

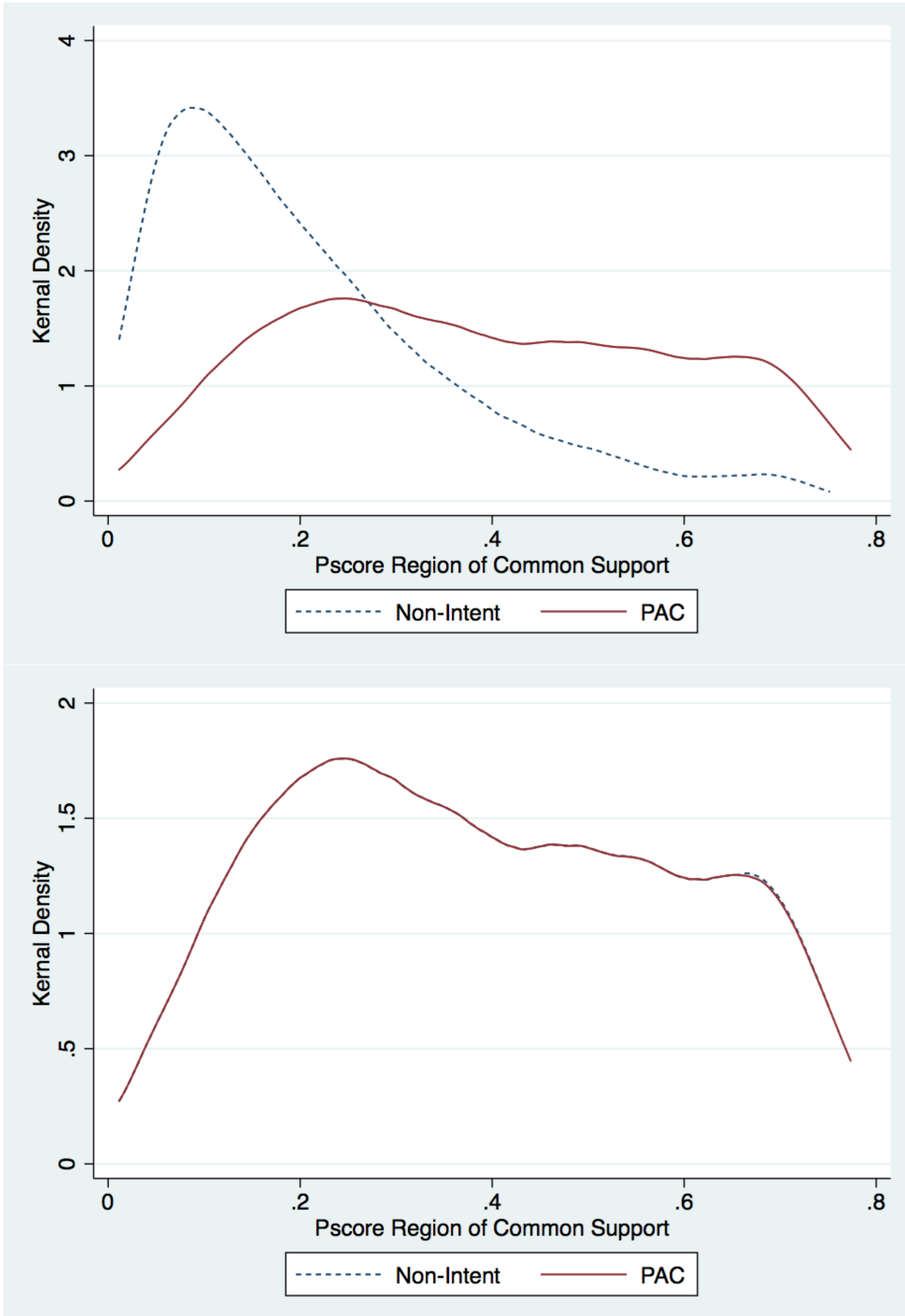

Figure 21. Pre- and Post-Match Kernel Density plots for *Past Account Creation*. The distance under each curve represents the full portion of the group with a particular pscore, and extends horizontally across the full range of pscores. The vertical distance between curves, the kernel density, measures the sample's proportional difference between the two groups. After applying the matched weighting there should be no discernable difference in curves horizontally or vertically, as is the case for this data.

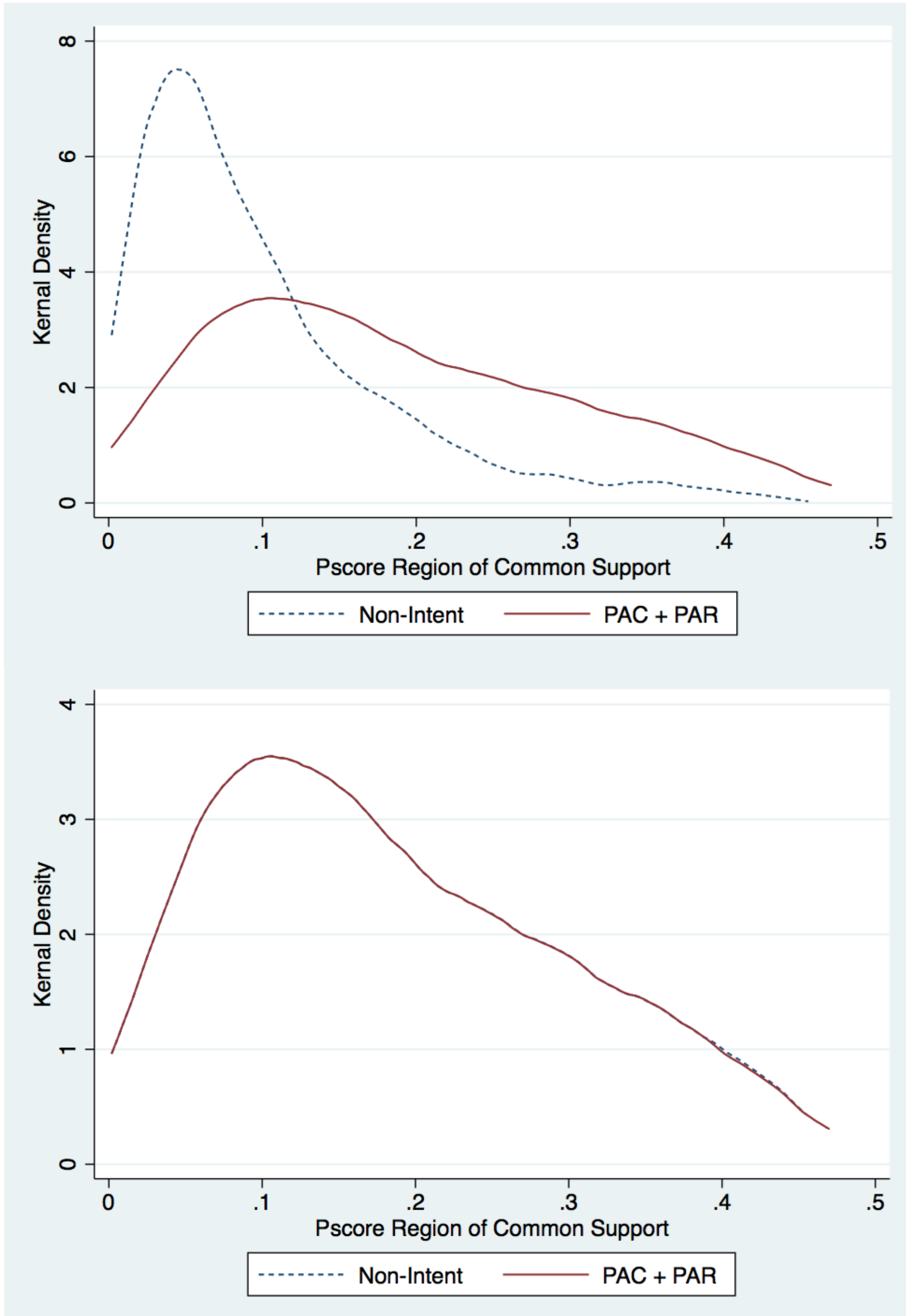

Figure 22. Pre- and Post-Match Kernel Density plot for *Past Account Creation* + *Past Asset Reallocation.* The distance under each curve represents the full portion of the group with a particular pscore, and extends horizontally across the full range of pscores. The vertical distance between curves, the kernel density, measures the sample's proportional difference between the two groups. After applying the matched weighting there should be no discernable difference in curves horizontally or vertically, as is the case for this data.

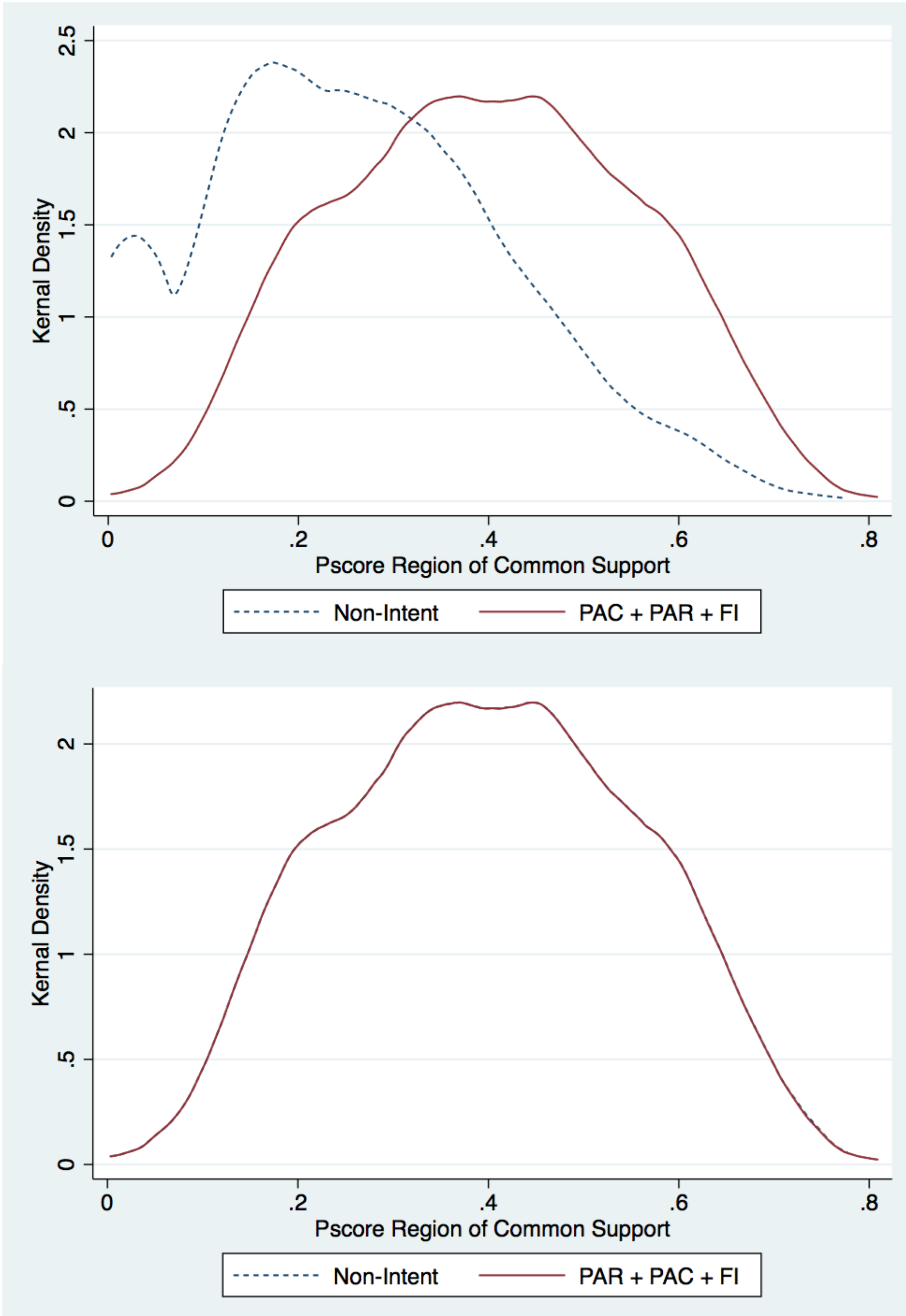

Figure 23. Pre- and Post-Match Kernel Density plot for *Past Account Creation* + *Past Asset Reallocation* + *Future Intention*. The distance under each curve represents the full portion of the group with a particular pscore, and extends horizontally across the full range of pscores. The vertical distance between curves, the kernel density, measures the sample's proportional difference between the two groups. After applying the matched weighting there should be no discernable difference in curves horizontally or vertically, as is the case for this data.

Appendix C – Typology Program's Reference Table

Appendix C.
List of Program Websites Used to Identify Operational Procedures

Program Name	Website Reference for Program Characteristics and Operational Procedures
Alaska Performance Grant	https://acpe.alaska.gov/FINANCIAL_AID/Grants_Scholarships/Alaska_Performance_Scholarship
Alabama Student Assistance Program	http://www.ache.state.al.us/Content/Departments/StudentAsst/StudentAsst.aspx
Arkadelphia Promise	http://arkadelphiapromise.com
Arkansas Academic Challenge Scholarship	http://scholarships.adhe.edu/scholarships/detail/academic-challenge-scholarships
El Dorado Promise	http://www.eldoradopromise.com
Great River Promise Scholarship	http://www.anc.edu/promise/
Great River Promise - Phillips	http://www.pccua.edu/admissions-financial-aid/scholarships/the-great-river-promise
School Counts!: Morrilton	http://ccschoolcounts.org
ASU Barack Obama Scholarship	https://students.asu.edu/obama
Promise of the Future	https://centralaz.edu/community/foundation/promise-for-the-future/
Adelante Promise	https://www.sac.edu/StudentServices/SantaAnaAdelante/Pages/default.aspx
Blue and Gold Opportunity Plan	http://admission.universityofcalifornia.edu/paying-for-uc/glossary/blue-and-gold/
Cal Grant A / Cal Grant B	http://www.csac.ca.gov/doc.asp?id=905
Claremont McKenna College	https://www.cmc.edu/news/claremont-mckenna-college-introduces-no-loan-policy
Connecticut College	http://aspen.conncoll.edu/news/3835.cfm
The Cuesta Promise	http://www.cuesta.edu/admissionsaid/cuestapromise/
The Fulfillment Fund	http://fulfillment.org/programs
Long Beach College Promise	http://www.longbeachcollegepromise.org
Oakland Promise	https://www.eastbaycollegefund.org/oakland-promise/
PACE Promise	http://thesanmarcospromise.org/programs/pace-promise/
Pomona College	https://www.pomona.edu/events/news/NewsItems/121207finaid.asp
San Francisco Promise	https://sfpromise.sfsu.edu
SBCC Promise	http://www.sbccpromise.org
Siskiyous Promise	http://www.siskiyous.edu/promise/
Stanford University	https://news.stanford.edu/news/2008/february20/finaid-022008.html
Valley-Bound Commitment	https://www.valleycollege.edu/student-services/specialized-counseling-services/valley-bound-commitment/
Ventura College Promise	http://www.venturacollege.edu/departments/administrative/foundation/programs/vc-promise
West Hills President's Scholars	http://www.westhillscollege.com/district/foundation/scholarships/presidents-scholars.asp
West Valley College Community Grant	http://westvalley.edu/community-grant/
Youth 2 Leaders Education Foundation	http://www.y2lef.org
Aims Community College Promise	https://www.aims.edu/foundation/scholarships/high-school/aims-promise-scholarship.php
Commitment to Colorado	http://www.csusystem.edu/commitment-to-colorado
Denver Scholarship Foundation	https://denverscholarship.org
Bridgeport Tuition Plan	https://www.fairfield.edu/undergraduate/financial-aid-and-tuition/scholarships-and-grants/
New Haven Promise	http://newhavenpromise.org
Wesleyan University	http://www.wesleyan.edu/admission/affording/how.html
DCTAG	https://osse.dc.gov/dctag
Delaware SEED Scholarship	https://www.dtcc.edu/admissions-financial-aid/financial-aid-scholarships/types-aid/seed
Inspire Scholarship	https://www.desu.edu/admissions/tuition-financial-aid/scholarships/inspire-scholarship
American Dream Scholarship	http://www.mdc.edu/financialaid/scholarships/american-dream.aspx
Bright Futures Scholarship Program	http://www.floridastudentfinancialaid.org/ssfad/bf/
Buffalo Scholarship Foundation	https://www.buffaloscholarshipfoundation.org
Machen Florida Opportunity	http://fos.ufsa.ufl.edu
Pensacola Pledge Scholars	http://uwf.edu/admissions/undergraduate/cost-and-financial-aid/awards-and-scholarships/pensacola-pledge/
Rosen Foundation Scholarship	https://www.tangeloparkprogram.com/programs/scholarship/
Emory Advantage	http://studentaid.emory.edu/types/grant-schol/emory-advantage.html
Georgia Tech Promise	https://www.finaid.gatech.edu/tech-promise
HOPE Scholarship / Zell Miller Grant	https://gsfc.georgia.gov/hope
Grinnell College	http://wm.grinnell.edu/cgi-bin/relish.dll/showrel?id=22&rDate=02/11/2008&dDate=2/11/2008

Appendix C. *cont.*

List of Program Websites Used to Identify Operational Procedures

Program Name	Website Reference for Program Characteristics and Operational Procedures
Chicago Star Scholarship	http://www.ccc.edu/departments/Pages/chicago-star-scholarship.aspx
Dell and Evelyn Carroll Scholarship	http://herald-review.com/news/local/macon-couple-s-endowment-to-fund-full-richland-scholarships-for/article_3b27091c-6b6a-11e2-a29c-001a4bcf887a.html
Galesburg Promise	http://www.sandburg.edu/Services/Financial-Aid/Foundation-Scholarships/Galesburg-Promise.html
Harper College Promise	http://goforward.harpercollege.edu/about/promise/index.php
Huskie Advantage Program	http://northernstar.info/campus/huskie-advantage-may-help-make-ends-meet-for-incoming-freshmen/article_77c37298-dca1-50fc-8ec2-dbf8e5171da3.html
Illinois Promise	http://osfa.illinois.edu/types-of-aid/illinois-promise
Northwestern University	http://www.northwestern.edu/newscenter/stories/2008/01/noloanpolicy.html
Odyssey Scholarship	https://odyssey.uchicago.edu
Peoria Promise	http://www.peoriapromise.org
Rockford Promise	http://www.rockfordpromise.org
UChicago Promise	https://promise.uchicago.edu
College Bound Scholarship	http://www.readysetgrad.org/college/college-bound-scholarship-program
Purdue Promise	https://www.purdue.edu/studentsuccess/specialized/purduepromise/index.html
Twnety-First Century Scholars	http://scholars.in.gov
** ISU 4U Promise	http://www.newswise.com/articles/more-than-a-promise-isu-4u-aims-to-offer-more-than-financial-assistance?channel=
Cardinal Covenant	http://www.wlky.com/article/uofl-celebrates-largest-gift-to-cardinal-covenant-program/3755663
Community Scholarship Program	https://westkentucky.kctcs.edu/academics/k12/csp.aspx
Hopkinsville Rotary Scholars	http://www.hopkinsvillerotary.com/scholars/
KEES	https://www.kheaa.com/website/kheaa/kees?main=1
Kentucky College Access Program Grant	https://www.kheaa.com/website/kheaa/cap?main=1
Louisville Rotary Club Scholarship	https://jefferson.kctcs.edu/news/rotary-club-of-louisville-to-promise-scholarships.aspx
School Counts!:Madisonville	https://madisonville.kctcs.edu/costs_and_financial_aid/scholarship_opportunities/school_counts/
Louisiana GO Grant	https://www.osfa.la.gov/go_grant.html
TOPS	https://www.osfa.la.gov/TOPS.htm
Amherst College	https://www.amherst.edu/admission/afford_amherst/index.html
B.U. Community Service Award	https://www.bu.edu/finaid/types-of-aid/scholarships-grants/need-based/bu-community-service-award/
College of Holy Cross	https://www.holycross.edu/sites/default/files/campaign-landing/resources/holy_cross_financial_aid_final.pdf
Harvard University	https://nonprofitquarterly.org/2013/11/08/harvard-initiative-to-attract-low-income-students-includes-free-tuition/
Massachusetts MASSGrant	http://www.mass.edu/osfa/programs/massgrant.asp
MIT	https://www.insidehighered.com/news/2012/08/20/mit-moves-away-aid-policy-which-low-income-students-dont-need-borrow
Tufts University	http://enews.tufts.edu/stories/116/2007/12/19/TuftsUniversityEliminatesLoansforLowerIncomeStudents
Williams College	https://communications.williams.edu/news-releases/williams-replaces-all-financial-aid-loans-with-grants/
Garrett County Scholarship Program	https://www.garrettcounty.org/commissioners/scholarship-program---garrett-college
Maryland Pathways	http://terp.umd.edu/2.2/interpretations/
Bowdoin College	http://www.bowdoin.edu/news/archives/1bowdoincampus/004745.shtml
Colby College	https://www.colby.edu/news/2011/10/27/amidst-student-debt-crisis-colby-reaffirms-no-loans/
State of Maine Grant	https://www.scholarships.com/financial-aid/college-scholarships/scholarships-by-state/maine-scholarships/state-of-maine-grant-program/
Baldwin Promise	http://www.baldwinpromise.org/content/baldwin-promise
Bay Commitment Scholarship	http://bayfoundation.org/scholarships/bay-commitment-scholarship/
Benton Harbor Promise	http://bentonharborpromise.com/about/about-eligibility/
Campus and Community	http://www.finlandia.edu/about/campus-community-together-good/
Detroit College Promise	http://www.detroitcollegepromise.com
Detroit Scholarship Fund	http://www.detroitchamber.com/econdev/education-and-talent/detroit-promise/
Hazel Park Promise	http://www.hazelpark.org/residents/promise_zone.php
Jackson Legacy	http://www.jacksoncf.org/page-1431733
Kalamazoo Promise	https://www.kalamazoopromise.com
Lansing Promise	http://lansingpromise.org
Legacy Scholars	http://www.kellogg.edu/admissions/legacyscholars/
Michigan M-PACT	http://www.ur.umich.edu/0405/Mar07_05/00.shtml

Appendix C. *cont.*

List of Program Websites Used to Identify Operational Procedures

Program Name	Website Reference for Program Characteristics and Operational Procedures
Michigan Tuition Grant	https://www.michigan.gov/documents/FactSheetMTG_153010_7.pdf
Michigan Tuition Incentive Program	http://www.michigan.gov/mistudentaid/0,4636,7-128-60969_61016-274565--,00.ht ml
Muskegon Promise	http://www.muskegonisd.org/career-college/promise/
Northport Promise	https://www.northportpromise.com
Pontiac Promise	http://www.pontiacpromisezone.org
Saginaw Promise	http://www.saginawpromise.org
Spartan Advantage	https://finaid.msu.edu/spad.asp
Carleton College	https://apps.carleton.edu/media_relations/press_releases/?story_id=391275
Minnesota State Grant	https://www.ohe.state.mn.us/mPg.cfm?pageID=138
Power of YOU	https://www.minneapolis.edu/Admissions/Power-of-YOU
Access Missouri Financial Assistance	https://dhe.mo.gov/ppc/grants/accessmo.php
Missouri A+ Scholarship Program	https://dhe.mo.gov/ppc/grants/aplusscholarship.php
Washington University St. Louis	https://source.wustl.edu/2008/02/wustl-to-expand-financial-aid-for-lowincome-families/
Mississippi Tuition Assistance Grant	http://riseupms.com/state-aid/mtag/
Appalachian ACCESS	https://studentlearningcenter.appstate.edu/access
Carolina Covenant	http://carolinacovenant.unc.edu
Davidson College	https://www.insidehighered.com/news/2007/03/19/davidson
Duke University	https://financialaid.duke.edu/newsupport
Pack Promise	https://financialaid.ncsu.edu/pack-promise/
VanGuarantee	https://www.vgcc.edu/fao/vanguarantee
North Dakota Academic Scholarship	https://www.ndus.edu/students/paying-for-college/grants-scholarships/
North Dakota Student Incentive Grant	https://www.ndus.edu/students/paying-for-college/grants-scholarships/
Collegebound Nebraska	http://collegeboundnebraska.com
Dartmouth College	http://www.dartmouth.edu/~news/releases/2010/02/08a.html
Cooperman College Scholarship	http://coopermanscholars.org
Newark College Promise	https://nhapromise.wordpress.com
New Jersey Tuition Aid Grant	http://www.hesaa.org/Pages/NJGrantsHome.aspx
School Counts!:Carney's	http://www.salemnj.org/schools/salem_high_school/guidance___counseling/s_c_h_o_o_l_c_o_u_n_t_s_
School Counts!:Cumberland	http://www.cccnj.edu/paying-college/school-counts
Princeton University	https://paw.princeton.edu/article/no-loan-pledge-decade-later
Legislative Lottery Scholarship/ 3% Bridge	http://www.hed.state.nm.us/students/lotteryscholarship.aspx
Govenrnor Quinn Millennium Scholarship	http://www.nevadatreasurer.gov/GGMS/GGMS_Home/
Columbia University	http://cc-seas.financialaid.columbia.edu/how/aid/works
Cornell University	http://news.cornell.edu/stories/2012/07/cornell-affirms-need-blind-admissions-aid-policies#boxes
New York State TAP	https://www.hesc.ny.gov/pay-for-college/apply-for-financial-aid/nys-tap.html
Rochester Promise	http://www.rochester.edu/news/show.php?id=7022
Say Yes to Education: Buffalo	http://sayyesbuffalo.org
Say Yes to Education: Syracuse	http://sayyessyracuse.org
Vassar College	https://alumsdigest.vassar.edu/issues/2008/04/affordability.html
Blue and Gold Scholar Award	https://www.utoledo.edu/financialaid/scholarships/pdfs/scholar_2017_2018/Blue%20and%20Gold%20T%20and%20C.pdf
Champion City Scholars Program	https://www.clarkstate.edu/about-clark-state/youth-outreach-programs/champion-city-scholars/
Kenyon College	http://www.kenyon.edu/x39073.xml
Miami Access Initiative	http://www2.northwest.k12.oh.us/docs2/ScholarshipInfo/MiamiAccessInitiative.htm
Montgomery Cty OH College Promise	http://www.mcocp.org
Oberlin College	https://www.oberlin.edu/newserv/08apr/access.html#gsc.tab=0&gsc.q=newserv%2008apr%20access&gsc.sort=
Ohio College Opportunity Grant	https://www.ohiohighered.org/ocog
Oklahoma Promise	http://www.okhighered.org/okpromise/
Oklahoma Tuition Aid Grant	https://www.okcollegestart.org/Financial_Aid_Planning/Oklahoma_Grants/Oklahoma_Tuition_Aid_Grant.aspx
Tulsa Achieves	http://www.tulsacc.edu/admissions-aid/admissions/tulsa-achieves

Appendix C. *cont.*

List of Program Websites Used to Identify Operational Procedures

Program Name	Website Reference for Program Characteristics and Operational Procedures
Bernard Daly Educational Fund	http://extension.oregonstate.edu/lake/sites/default/files/jamie_m._davis_rules_and_reg_bernard_daly_fund.pdf
Future Connect	https://www.pcc.edu/future-connect/
Oregon Opportunity Grant	https://oregonstudentaid.gov/oregon-opportunity-grant.aspx
Oregon Promise	https://oregonstudentaid.gov/oregon-promise.aspx
Pathway Oregon	https://pathwayoregon.uoregon.edu
50th Anniversary Scholars	https://www.ccp.edu/paying-college/tuition-assistance-programs/50th-anniversary-scholars-program
CORE Promise	https://corescholars.org/promise/
Haverford College	https://www.haverford.edu/college-communications/news/haverford-college-replace-loans-grants-incoming-first-year-students
Lafayette College	https://www.lafayette.edu/news.php/view/11885/
Lehigh University	https://www1.lehigh.edu/news?iNewsID=2654&strBack=/default.asp
Morgan Success Scholarship	https://www.lccc.edu/tuition-financial-aid/scholarships/morgan-success-scholarship
Philadelphia Education Fund	http://www.philaedfund.org
Pittsburgh Promise	https://www.pittsburghpromise.org
Swathmore College	http://www.swarthmore.edu/news-archive-2007-2008/swarthmore-eliminates-loans-financial-aid-awards
UPenn	https://news.upenn.edu/article.php?id=1287
Brown University	http://www.brown.edu/Administration/News_Bureau/2007-08/07-105.html
Crusade of Rhode Island	http://thecollegecrusade.org/tccri/
South Dakota Jump Start Scholarship	https://www.sdbor.edu/student-information/Pages/Jump-Start-Scholarship.aspx
South Dakota Opportunity Scholarship	https://sdos.sdbor.edu
Ayers Foundation Scholars Program	http://www.ayersscholars.org
Dyer County Promise Scholarship	http://www.dscc.edu/node/7061
Educate and Grow	http://www.northeaststate.edu/Financial-Aid/Internal-Scholarships/Educate-and-Grow-Scholarship/
Opportunity Vanderbilt	https://giving.vanderbilt.edu/oppvu/
Tennessee Pledge	http://tntoday.utk.edu/2005/11/10/tennessee-pledge-scholarships-help-students-attend-ut/
Tennessee Promise	http://tnpromise.gov
tnAchieves (Knox Achieves)	https://tnachieves.org
William Jennings Bryan Opportunity	https://www.facebook.com/BryanCollege/videos/511669513931/
Aggie Assurance	http://financialaid.tamu.edu/Aggie-Assurance
Bobcat Promise	http://www.finaid.txstate.edu/bobcatpromise
Lamar Promise	https://www.lamar.edu/financial-aid/types-of-aid/grants/lamar-promise.html
Rice University	http://news.rice.edu/2008/12/18/rice-increases-no-loan-threshold-to-80000-2/
Rusk TJC Citizens Promise	https://www.tjc.edu/ruskpromise
Sacred Heart University	http://www.sacredheart.edu/404/?referrer=www.sacredheart.edu/pages/23744_sacred_heart_university_to_offer_tuition_free_education_to_low_income_fairfield_county_students.cfm
TEXAS Grant	https://www.google.com/search?client=safari&rls=en&q=TEXAS+Grant&ie=UTF-8&oe=UTF-8
UTEP Promise	https://academics.utep.edu/Default.aspx?tabid=44628
Regent Scholarship	https://scholarships.tamu.edu/Scholarship-Programs/Regents-Scholars
SLCC Promise	https://www.slcc.edu/promise/
Beacon of Hope	http://beaconofhopelynchburg.org/scholarships/
Virginia Guaranteed Assistance	http://www.schev.edu/docs/default-source/tuition-aid-section/financial-aid/vgap-fact-sheet.pdf
William and Mary Promise/Gateway	http://www.wm.edu/sites/wmpromise/
13th Year Promise	http://www.southseattle.edu/13th-year/
College Success Foundation	https://www.collegesuccessfoundation.org
Husky Promise	https://www.washington.edu/huskypromise/
Passport for Foster Youth Promise	http://www.wsac.wa.gov/passport-foster-youth
Seattle Promise	http://foundation.seattlecentral.edu/impact/scholarships
Shoreline Scholars	https://www.shoreline.edu/shoreline-scholars/
Washington College Bound Scholarship	http://www.wsac.wa.gov/college-bound
WA State Need Grant	http://www.wsac.wa.gov/state-need-grant
Nicolet Promise	http://www.nicoletcollege.edu/about/features/nicolet-promise.html

Appendix C. *cont.*

List of Program Websites Used to Identify Operational Procedures

Program Name	Website Reference for Program Characteristics and Operational Procedures
Wisconsin Tuition Assistance Grant	http://www.heab.state.wi.us/programs.html
WITC Promise	http://www.witc.edu/foundationcontent/pdfs/WITCPromiseApplicationForm2017.pdf
Hathaway Scholarship	https://edu.wyoming.gov/beyond-the-classroom/college-career/scholarships/hathaway/
West Virginia Promise Scholarship	https://www.cfwv.com/Financial_Aid_Planning/Scholarships/Scholarships_and_Grants/West_Virginia_PROMISE.aspx

Appendix D – Carroll Scholarship Difference-in-Difference Prior Year Trend Regression Result Tables

Table 58.

OLS Regression naïve Models for Prior Year trends of Postsecondary Credit Hours Attempted at Richland: MERIDIAN student treatment condition: Interaction with Academic Year: separated by High School Grade Point Average Quartile

	Credit Hours: Attempted			
	H.S. GPA: Q1	H.S. GPA: Q2	H.S. GPA: Q3	H.S. GPA: Q4
Model	(1.085-2.720)	(2.722-3.200)	(3.204-3.701)	(3.710-5.000)
(Std. Error)	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
MERIDIAN x 2010	-1.647	-0.960	-3.789	-3.215
	(3.237)	(2.665)	(2.746)	(1.972)
MERIDIAN x 2011	2.793	0.191	0.825	-5.755
	(1.841)	(2.797)	(2.514)	(5.252)
MERIDIAN x 2012	-0.415	-3.179	-3.173	-5.271
	(2.161)	(2.333)	(2.280)	(3.663)
MERIDIAN x 2013	0.819	-0.864	3.305	-3.742**
	(2.280)	(2.367)	(2.844)	(1.746)
MERIDIAN x 2014	4.289**	2.550	3.509	-1.213
	(1.942)	(1.989)	(2.269)	(2.069)
MERIDIAN x 2015	5.120***	0.368	7.615***	-1.366
	(1.829)	(1.795)	(2.616)	(1.673)
Other Aid Amount ($100)	0.00270***	0.00291***	0.00359***	0.00442***
	(0.000247)	(0.000210)	(0.000231)	(0.000149)
Pell Grant Recipient	-4.289***	-4.971***	-3.677***	-3.824***
	(0.792)	(0.982)	(1.124)	(1.037)
Pell Grant Amount ($100)	0.00311***	0.00278***	0.00223***	0.00170***
	(0.000166)	(0.000212)	(0.000244)	(0.000248)
Dual Credit Enrollee	-2.080***	-2.984***	-2.602***	-1.905***
	(0.549)	(0.699)	(0.645)	(0.533)
Male	0.606	0.922	2.099***	0.431
	(0.499)	(0.575)	(0.582)	(0.528)
White	-1.605	1.120	-4.032*	0.380
	(1.418)	(1.197)	(2.068)	(1.687)
African-American	-2.843*	-0.604	-7.125***	-4.945**
	(1.486)	(1.401)	(2.297)	(2.238)
Hispanic	-3.890	3.562	-10.98***	-0.820
	(2.401)	(5.542)	(2.880)	(2.812)
Two or More Identified	-4.007**	2.421	-7.115***	-1.365
	(1.618)	(1.994)	(2.538)	(2.057)
Constant	15.23***	15.24***	19.11***	13.08***
	(1.990)	(1.794)	(2.429)	(2.036)
Non-Meridian High School Dummy	Yes	Yes	Yes	Yes
Academic Year Fixed Effects	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	175	110	103	36
N. Control (In-District)	836	889	895	952
Observations	1,011	999	998	988
R-squared	0.381	0.307	0.384	0.548

Note. Robust standard errors in parentheses. *MERIDIAN* x Academic Year is a dummy variable. For instance, *Meridian x 2010* = 1 if *Meridian*= 1 and if the dependent variable occurs in academic year 2010 (*2010*= 1). If either equation is untrue, the interaction term *Meridian x 2010*= 0. Non-Dual Credit, Female, and All Other are the omitted variable categories. 2015 is the omitted Academic Year Fixed Effect category. School ID Number 5625 is the omitted Non-Meridian High School dummy variable. Coefficients for *Carroll Scholarship Amount*, Other Aid Amount, and Pell Grant Amount are multiplied by 100 to signify the impact of $100 dollars in aid award. Standard errors for *Carroll Scholarship Amount*, Other Aid Award, and Pell Grant Amount are not adjusted.
*** p<0.01, ** p<0.05, * p<0.1.

Table 59.

OLS Regression naïve Models for Prior Year trends of Postsecondary Credit Hours Earned at Richland: MERIDIAN student treatment condition: Interaction with Academic Year: separated by High School Grade Point Average Quartile

	Credit Hours: Earned			
	H.S. GPA: Q1	H.S. GPA: Q2	H.S. GPA: Q3	H.S. GPA: Q4
Model	(1.085-2.720)	(2.722-3.200)	(3.204-3.701)	(3.710-5.000)
(Std. Error)	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
MERIDIAN x 2010	-2.023	-1.651	-3.169	-2.028
	(2.224)	(2.481)	(2.691)	(2.049)
MERIDIAN x 2011	0.543	-2.830	0.229	-4.911
	(1.702)	(2.411)	(2.894)	(5.088)
MERIDIAN x 2012	0.317	-3.552	-2.679	-5.022
	(1.922)	(2.381)	(2.179)	(4.044)
MERIDIAN x 2013	3.238	-0.178	2.314	-3.164*
	(2.171)	(2.208)	(2.809)	(1.692)
MERIDIAN x 2014	5.592***	1.943	2.837	-3.162
	(1.882)	(1.986)	(2.171)	(2.911)
MERIDIAN x 2015	5.989***	0.686	6.394***	-0.585
	(1.746)	(1.847)	(2.460)	(2.200)
Other Aid Amount ($100)	0.205***	0.265***	0.366***	0.452***
	(0.000266)	(0.000205)	(0.000221)	(0.000159)
Pell Grant Recipient	-6.057***	-5.278***	-5.512***	-3.644***
	(0.815)	(1.046)	(1.019)	(1.014)
Pell Grant Amount ($100)	0.314***	0.271***	0.245***	0.152***
	(0.000185)	(0.000235)	(0.000246)	(0.000246)
Dual Credit Enrollee	-1.350**	-2.209***	-1.459**	-1.525***
	(0.539)	(0.704)	(0.664)	(0.554)
Male	0.216	0.733	2.340***	0.368
	(0.484)	(0.574)	(0.582)	(0.532)
White	-1.085	0.486	-3.658**	-0.584
	(2.290)	(1.237)	(1.802)	(1.614)
African-American	-2.592	-2.062	-6.762***	-6.010***
	(2.311)	(1.450)	(2.145)	(2.255)
Hispanic	-3.063	4.773	-10.83***	-1.681
	(3.230)	(5.480)	(2.446)	(2.115)
Two or More Identified	-3.625	1.198	-7.077***	-2.666
	(2.378)	(1.878)	(2.351)	(2.000)
Constant	11.28***	12.99***	16.84***	12.44***
	(2.654)	(1.787)	(2.216)	(2.038)
Non-Meridian High School Dummy	Yes	Yes	Yes	Yes
Academic Year Fixed Effects	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	175	110	103	36
N. Control (In-District)	836	889	895	952
Observations	1,011	999	998	988
R-squared	0.331	0.293	0.393	0.553

Note. Robust standard errors in parentheses. *MERIDIAN* x Academic Year is a dummy variable. For instance, *Meridian x 2010* = 1 if *Meridian*= 1 and if the dependent variable occurs in academic year 2010 (*2010*= 1). If either equation is untrue, the interaction term *Meridian x 2010*= 0. Non-Dual Credit, Female, and All Other are the omitted variable categories. 2015 is the omitted Academic Year Fixed Effect category. School ID Number 5625 is the omitted Non-Meridian High School dummy variable. Coefficients for *Carroll Scholarship Amount*, Other Aid Amount, and Pell Grant Amount are multiplied by 100 to signify the impact of $100 dollars in aid award. Standard errors for *Carroll Scholarship Amount*, Other Aid Award, and Pell Grant Amount are not adjusted.
*** p<0.01, ** p<0.05, * p<0.1.

Table 60.

OLS Regression naïve Models for Prior Year trends of Postsecondary Credit Hours Withdrawn at Richland: MERIDIAN student treatment condition: Interaction with Academic Year: separated by High School Grade Point Average Quartile

	Credit Hours: Withdrawn			
Model	H.S. GPA: Q1 (1.085-2.720)	H.S. GPA: Q2 (2.722-3.200)	H.S. GPA: Q3 (3.204-3.701)	H.S. GPA: Q4 (3.710-5.000)
(Std. Error)	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
MERIDIAN x 2010	0.145	0.653	-0.879	-1.253**
	(2.047)	(1.129)	(0.986)	(0.558)
MERIDIAN x 2011	2.352*	2.843*	0.823	-0.780
	(1.356)	(1.502)	(1.105)	(0.506)
MERIDIAN x 2012	-1.112	0.332	-0.413	-0.674*
	(1.273)	(1.739)	(0.754)	(0.387)
MERIDIAN x 2013	-2.429**	-0.827	0.786	-0.611
	(1.041)	(0.825)	(1.094)	(0.418)
MERIDIAN x 2014	-1.487	0.562	0.346	1.868
	(1.144)	(0.740)	(0.591)	(1.383)
MERIDIAN x 2015	-1.068	-0.355	0.948	-0.851
	(1.013)	(0.876)	(0.914)	(0.774)
Other Aid Amount ($100)	0.000582***	0.000267**	-0.000117	-9.42e-05
	(0.000142)	(0.000134)	(7.38e-05)	(6.58e-05)
Pell Grant Recipient	1.778***	0.420	1.055*	-0.180
	(0.607)	(0.660)	(0.555)	(0.658)
Pell Grant Amount ($100)	-7.74e-05	2.81e-05	-8.61e-05	0.000165
	(0.000154)	(0.000160)	(0.000146)	(0.000167)
Dual Credit Enrollee	-0.725**	-0.742**	-1.154***	-0.396
	(0.346)	(0.363)	(0.340)	(0.272)
Male	0.451	0.281	-0.00616	0.0720
	(0.306)	(0.280)	(0.275)	(0.249)
White	-0.592	0.498	0.0993	0.924*
	(1.319)	(0.776)	(0.754)	(0.485)
African-American	-0.459	1.303	0.342	1.132
	(1.357)	(0.871)	(0.954)	(0.770)
Hispanic	-0.885	-1.356	-0.424	0.859
	(1.609)	(0.919)	(1.203)	(1.315)
Two or More Identified	-0.435	0.960	0.421	1.356
	(1.500)	(1.104)	(1.150)	(0.850)
Constant	4.248***	2.391**	2.068**	0.777
	(1.607)	(0.990)	(0.874)	(0.665)
Non-Meridian High School Dummy	Yes	Yes	Yes	Yes
Academic Year Fixed Effects	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	175	110	103	36
N. Control (In-District)	836	889	895	952
Observations	1,011	999	998	988
R-squared	0.083	0.070	0.077	0.068

Note. Robust standard errors in parentheses. *MERIDIAN* x Academic Year is a dummy variable. For instance, *Meridian x 2010* = 1 if *Meridian*= 1 and if the dependent variable occurs in academic year 2010 (*2010*= 1). If either equation is untrue, the interaction term *Meridian x 2010*= 0. Non-Dual Credit, Female, and All Other are the omitted variable categories. 2015 is the omitted Academic Year Fixed Effect category. School ID Number 5625 is the omitted Non-Meridian High School dummy variable. Coefficients for *Carroll Scholarship Amount*, Other Aid Amount, and Pell Grant Amount are multiplied by 100 to signify the impact of $100 dollars in aid award. Standard errors for *Carroll Scholarship Amount*, Other Aid Award, and Pell Grant Amount are not adjusted.

*** p<0.01, ** p<0.05, * p<0.1.

Table 61.

OLS Regression naïve Models for Prior Year trends of Postsecondary Credit Hours Failed at Richland: MERIDIAN student treatment condition: Interaction with Academic Year: separated by High School Grade Point Average Quartile

	Credit Hours: Failed			
	H.S. GPA: Q1	H.S. GPA: Q2	H.S. GPA: Q3	H.S. GPA: Q4
Model	(1.085-2.720)	(2.722-3.200)	(3.204-3.701)	(3.710-5.000)
(Std. Error)	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
MERIDIAN x 2010	1.802	-0.631	-0.650**	-0.351
	(1.304)	(0.510)	(0.285)	(0.275)
MERIDIAN x 2011	1.305	-0.454	-0.545	-0.227
	(0.817)	(0.668)	(0.368)	(0.208)
MERIDIAN x 2012	0.483	-0.629	-0.743***	-0.309*
	(0.550)	(0.400)	(0.287)	(0.173)
MERIDIAN x 2013	-0.716	-0.408	0.0290	-0.0721
	(0.515)	(0.370)	(0.356)	(0.180)
MERIDIAN x 2014	1.219	-0.108	0.835	1.209
	(0.754)	(0.565)	(0.781)	(0.858)
MERIDIAN x 2015	0.854	-0.608	-0.362	0.0972
	(0.641)	(0.490)	(0.250)	(0.539)
Other Aid Amount ($100)	0.000208**	6.89e-05	1.74e-06	-2.16e-05
	(0.000100)	(7.12e-05)	(4.09e-05)	(3.04e-05)
Pell Grant Recipient	0.646*	-0.550*	-0.0826	0.182
	(0.388)	(0.318)	(0.227)	(0.279)
Pell Grant Amount ($100)	6.80e-05	0.000281***	3.46e-05	9.51e-05
	(0.000104)	(9.25e-05)	(5.22e-05)	(8.25e-05)
Dual Credit Enrollee	-0.551**	-0.341	-0.440**	-0.160
	(0.242)	(0.227)	(0.172)	(0.136)
Male	0.0877	-0.193	0.105	0.242**
	(0.205)	(0.169)	(0.150)	(0.120)
White	0.486	0.0239	-0.717	0.112
	(0.908)	(0.393)	(0.675)	(0.241)
African-American	0.327	0.0244	-0.581	-0.208
	(0.939)	(0.506)	(0.725)	(0.507)
Hispanic	-0.293	-0.295	-1.359**	0.407
	(1.138)	(0.465)	(0.680)	(0.372)
Two or More Identified	1.357	0.167	-0.768	0.211
	(1.118)	(0.577)	(0.818)	(0.345)
Constant	0.491	0.937*	1.434**	0.152
	(1.013)	(0.565)	(0.714)	(0.294)
Non-Meridian High School Dummy	Yes	Yes	Yes	Yes
Academic Year Fixed Effects	Yes	Yes	Yes	Yes
N. Treatment (Meridian)	175	110	103	36
N. Control (In-District)	836	889	895	952
Observations	1,011	999	998	988
R-squared	0.068	0.061	0.086	0.069

Note. Robust standard errors in parentheses. *MERIDIAN* x Academic Year is a dummy variable. For instance, *Meridian x 2010* = 1 if *Meridian*= 1 and if the dependent variable occurs in academic year 2010 (*2010*= 1). If either equation is untrue, the interaction term *Meridian x 2010*= 0. Non-Dual Credit, Female, and All Other are the omitted variable categories. 2015 is the omitted Academic Year Fixed Effect category. School ID Number 5625 is the omitted Non-Meridian High School dummy variable. Coefficients for *Carroll Scholarship Amount*, Other Aid Amount, and Pell Grant Amount are multiplied by 100 to signify the impact of $100 dollars in aid award. Standard errors for *Carroll Scholarship Amount*, Other Aid Award, and Pell Grant Amount are not adjusted.

*** p<0.01, ** p<0.05, * p<0.1.