2017-01-01

Dual Enrollment Participation in the United States: Findings from the High School Longitudinal Study of 2009

Luis Eduardo Rivera
University of Texas at El Paso, riveraluiseduardo@icloud.com

DUAL ENROLLMENT PARTICIPATION IN THE UNITED STATES: FINDINGS FROM THE HIGH SCHOOL LONGITUDINAL STUDY OF 2009

LUIS EDUARDO RIVERA

Master's Program in Economics and Finance

APPROVED:

____
Nathan J. Ashby, Ph.D., Chair

____
Stephen A. Kotok, Ph.D.

____
Timothy P. Roth, Ph.D.

____
Charles Ambler, Ph.D.
Dean of the Graduate School

Dedication

I dedicate this achievement to my wife Rocio and our children Adi, Esli, and Yeshua. I also dedicate this to my parents Luis and Rosa and to my siblings Jonathan and Lizette. God has blessed me infinitely with a beautiful family.

DUAL ENROLLMENT PARTICIPATION IN THE UNITED STATES: FINDINGS FROM THE HIGH SCHOOL LONGITUDINAL STUDY OF 2009

by

LUIS EDUARDO RIVERA, BBA

THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science

Department of Economics and Finance

THE UNIVERSITY OF TEXAS AT EL PASO

August 2017

Acknowledgements

Dr. Ashby has shown me great support throughout my Economics undergraduate and graduate journey. Thank you Dr. Ashby. Likewise, I would like to express my deepest gratitude to Dr. Kotok for trusting me with access to the data herein and providing unconditional support for the completion of this thesis project. This journey would have never been possible without the best colleagues ever: Jesus Mendoza, Macie Subia, Esmeralda Orozco, Angel Moreno, Lisa Cordero, Felipe Mejia, and Jose Bautista. You are the best fellow students and friends. Lastly, I want to thank Dr. Roth for his inspiration to pursue Economics as a lifelong endeavor, and Dr. Fullerton for challenging my colleagues and me to be the best students we could be.

Abstract

Today, dual enrollment programs are ubiquitous in the United States' secondary educational system. As a form of accelerated coursework, policy makers and school districts push dual enrollment as a means to improve college readiness and attainment. This paper studies the composition and characteristics of dual enrollment participants in the United States. Employing the High School Longitudinal Study of 2009 restricted dataset, three discrete logistic models are created to estimate the probability of a high school student participating in any dual enrollment coursework across the United States. The results from these models suggest that gender, prior academic achievement, and family socioeconomic status are the strongest predictors of dual enrollment program participation. A discussion of the research and policy implications of these findings follows.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Dual credit and dual enrollment programs have grown significantly in the United States for the past few decades. As a form of advanced coursework, Dual Enrollment[1] (Allen, 2010) has become commonplace with all states offering some form of dual credit as an option for high school students. While other alternatives such as Advanced Placement (AP) and International Baccalaureate (IB) remain available, education stakeholders increasingly view dual credit or dual enrollment programs as a means to improve college preparedness, attainment and address the high school to college gap. Dual enrollment (DE) programs often require the coordination of postsecondary institutions with secondary schools to facilitate the delivery of college coursework as early as a student's sophomore year of high school.

Advanced and accelerated coursework in the form of dual enrollment has become ubiquitous in the U.S. educational system. Recent national surveys illustrate the prevalence of DE in the U.S. In 2013, the National Center for Education Statistics (NCES) reported nationally representative data from two surveys: "Dual Credit and Exam-Based Courses in U.S. Public High Schools: 2010-11" (Thomas, Marken, Gray, & Lewis, 2013) and "Dual Enrollment Programs and Courses for High School Students at Postsecondary Institutions: 2010-11" (Marken, Gray, & Lewis, 2013). The previous survey reported about 1.4 million dual credit student enrollments and 3.5 million enrollments in AP or IB courses approximately. The latter indicated around 1.22 million high school students taking college credit courses at two and four-year degree granting institutions. The numbers are hardly negligible. Broadly, these figures reveal the efforts of parents, agencies, policymakers, and all other stakeholders, in creating an educated and increasingly credentialed society. It is, therefore, pertinent to understand the mechanisms and consequences of these programs.

[1] For this research endeavor, dual enrollment and dual credit will refer to coursework taken by students during high school which simultaneously confers them college-level credit upon successful completion. Moreover, regardless of the coursework delivery location –community college, online, neighboring high school campus, or others.

There is extensive literature pointing to the importance of human capital accumulation through schooling and its positive effects on lifetime earnings (Card, 1999; Heckman, Lochner, & Todd, 2003; Katz & Murphy, 1992; Mincer, 1974). Higher education levels and earnings, lead to higher economic and social ranks. It creates a virtuous circle in which educated parents make private human capital investments in their children such as tutoring or moving to better neighborhoods (Lareau, 2011). These children will, in turn, do the same for their offspring. Contrariwise, lack of opportunity and access can deny low-income families educational attainment with all its future benefits. Poverty traps and low educational attainment can become generational thus contributing to inequality (Ceroni, 2001; Durlauf, 1996). Consequently, the creation and development of programs which not only help underrepresented students achieve a post-secondary degree but also procure access to all student populations have become a priority for school agencies, districts, and administrators. Indeed, educational policy making has focused on making advanced and accelerated programs available to as many students as possible, particularly, disadvantaged students (Department of Education Press Office, 2016; No Child Left Behind [NCLB], 2002).

Funding and support for advanced coursework exist in major federal education reform and mandates. The No Child Left Behind Act created under the President George W. Bush's administration appropriated funding to cover AP test fees and set the goal of providing access to underrepresented groups (No Child Left Behind [NCLB], 2002). Subsequently, President Barack Obama's administration went further in supporting advanced coursework by proposing that Pell Grants be extended to cover DE courses (Department of Education Press Office, 2016).

Another essential theme in education policy and research is that of addressing and attempting to understand the achievement gap. The achievement gap is the disparity observed in the educational performance and attainment between dissimilar student groups. This phenomenon is pronounced along racial, gender and socioeconomic status characteristics of students. The gaps in education among the traits mentioned above have been the target of billions of dollars in education investment through many policies, to raise those at the bottom. Dual enrollment has

increasingly been touted by education policy makers as an effective tool to close the educational gap. Empirical studies on the benefits of dual enrollment classes and programs have shown benefits to low-income, racial minority and other underrepresented student populations (An, 2012; Haskell, 2016; Hugo, 2001). Nevertheless, while most studies on DE aim to measure its ‘treatment effects’ on traditionally disadvantaged groups; there are few studies, if any, exploring the ‘a priori’ characteristics and composition of dual enrollment participant populations.

The aim of this research endeavor is to analyze dual enrollment participation in the United States. This study uses the High School Longitudinal Study of 2009 data set (HSLS:09), a nationally representative sample, to examine the student characteristics influencing the probability of a student participating in dual credit coursework. Currently, there is no other empirical study which utilizes the HSLS:09 data set to investigate dual enrollment themes including dual credit access and participation. Such an analysis can shed light on this form of advanced coursework in a national context. It can also serve as a guide for the potential improvements as it refers to access to dual enrollment coursework which could contribute to closing the achievement and high school to college gap.

The models employed in this paper suggest that prior achievement as measured by Grade Point Average (GPA) in the 9^{th} grade and family socioeconomic status (SES) are primary and strong predictors of student participation in dual enrollment coursework. Simultaneously, the estimation results indicate that females participate in dual enrollment at higher rates than their male counterparts. These results are consistent when controlling for race/ethnicity and unobserved state-effects. Therefore, this paper could serve to gauge access to dual enrollment programs, and perhaps more importantly; it raises the question about which student populations eventually benefit from dual enrollment participation under the current design and delivery mechanisms of DE programs.

Chapter 2: Dual Enrollment Literature Review

Historical Context

Dual enrollment (DE) was first implemented in the United States in the 1980s as an option for students wanting to take rigorous coursework that would allow them to obtain college-level credit. States began putting policies in place facilitating high school students' course-taking at local community colleges. Minnesota is considered a pioneer in implementing the first statewide dual enrollment policy and it continues to expand its programs. The state of Washington followed in 1990. Moreover, gradually, DE programs and policies emerged in more states (Boswell, 2001). According to the latest information available, forty-seven states and the nation's capital have statutory provisions and regulations ruling over one or more statewide dual enrollment programs or policies. The remaining three states leave DE policies to the discretion of localities and their pertinent postsecondary institutions or systems (Education Commission, 2016).

Growth in DE programs and policies has been remarkably aggressive in recent years. Although it is difficult to know with precision the total amount of high schools offering dual credit options across the United States, some statistics illustrate the ubiquity of these programs. For example, the National Alliance of Concurrent Enrollment Partnerships (NACEP) states that DE had an annual growth of seven percent from 2003-2011 and that four out of five high schools offer college-level courses. Therefore, it is reasonable to believe that given the progressive adoption of DE across the US, it is also becoming institutionalized.

Supporters propose that DE increases college readiness (Hoffman, Vargas, & Santos, 2009). When students take college-level courses during high school, it eases the transition into a two or four-year institution. Participating in DE gives students a 'head start' in both content and credits and therefore increases the likeliness of attaining a postsecondary degree (Karp, Calcagno, Hughes, Jeong, & Bailey, 2007). Given the benefits of DE, inclusiveness, and access for underrepresented students is fundamental to the design and implementation of DE programs (Cassidy, Keating, & Young, 2010). Thus, research examining the equity in the distribution of dual enrollment programs is necessary. Furthermore, research on equal access to DE programs should

precede efforts assessing whether minorities, females or low socioeconomic background students benefit from DE programs.

PREVIOUS RESEARCH

The number of empirical studies analyzing dual enrollment are varied in scale, methodology, and focus. Some of the most relevant research on the subject comes from state-wide and national longitudinal empirical studies. One of the first major papers in DE was from Columbia University, and it estimated the outcomes of DE in Florida and New York (Karp et al., 2007). The researchers employed a non-experimental design and applied ordinary least squares and logistic methods. The authors found that in Florida, DE participation has a positive effect on the probability of a student completing high school and enrolling in college. Karp et al. (2007) utilized a large data set and controls for several key variables such as economic background, age, race, gender, and GPA among others. The authors found positive relationships between DE and enrollment to postsecondary schools after graduation. Additionally, Karp et al. comment that given their findings, DE holds promise for students from all backgrounds including those from underprivileged backgrounds. Speroni (2011), conducted a study utilizing longitudinal data from Florida. Her paper researched the effects of DE on tertiary degree attainment. The author found that students participating in such program were more likely to enroll in college than those students that did not. Another significant finding by Speroni was concerning the effectiveness of DE on minorities. The author found that minority students participating in DE were 6.1 percent more likely to attain a bachelor degree and 6.5 percent more likely to enroll in a four-year college while the numbers were 7.6 and 7.1 percent for non-minority students. Speroni found no significant difference between minority and non-minority DE participants on enrollment to postsecondary schools after high school.

Two noteworthy studies utilize nationally representative samples (An, 2012; Swanson, 2007). Both utilized the National Education Longitudinal Study of 1988 (NELS:88). Swanson (2008) finds that DE positively affects the likelihood of attending college as well as persistence

leading to the completion of a four-year degree. The author controlled for age, gender, ethnicity, SES among other relevant variables. Swanson developed a causal model to find the effects of dual enrollment on persistence, time to degree, credit accumulation and degree attainment. Under this causal model framework, the author created twenty-one logistic regression equations to estimate the direct and total effects of DE on a broad range of variables. Swanson reported overall benefits from DE participation such as a high percentage of students enrolling in college shortly after high school. Furthermore, Swanson found positive effects on males and Hispanic DE participants in terms of post-secondary enrollment after high school or persistence in college compared to female and white students respectively. Lastly, Swanson proposed as important to further study the low male participation in DE programs and enrollment to postsecondary education.

An (2012) estimated the effect of DE on a four-year degree attainment. He found that overall, DE increased the student probability of attaining any postsecondary degree by 7 percent. Another relevant finding by An is that those who participated in DE were 8 percent more likely to earn a college degree compared to those who did not. The author found that parental education exerts the largest influence on a student opting into DE coursework. The estimations by An reveal that first generation students enrolled in DE coursework are more likely to attain a college degree compared to those who did not. An (2012) found "partial support" that first generation students gain more than students from higher parental education households. However, after supplemental analyses, the author found that students from college-educated parents will likely enroll and attain a postsecondary degree regardless of DE participation. Thus, An's (2012) research asserts the importance of creating DE policies that principally target low-income schools. Not less importantly, An found that the benefits of dual credit course accumulation subside at six courses.

Two recent state-wide studies have emerged in the last five years (Allen & Dadgar, 2012; Giani, Alexander, & Reyes, 2014). Both utilized comprehensive data sets which allowed the researchers to build comprehensive empirical models. Allen and Dadgar (2012) used a quasi-experimental approach to study the City University of New York dual enrollment program by the name of College Now. The data set for this study allowed the researchers to control for what they

describe as an “exceptionally rich set of demographic and academic achievement indicators” (Allen & Dadgar, 2012). The researchers set out to find the impact of DE on college credit accumulation, retention, and GPA. They concluded that DE might increase the time to attainment, improve college GPA and increases accumulation of college credits positively. Giani, Alexander, and Reyes (2014) estimated the impact of dual credit on first to second-year resilience, attainment among other outcomes.

Any effective public policy should be constructed from and informed by contextual and empirical research. The literature discussed above meets such criteria. Furthermore, it also seems to form a consensus that DE is a policy worthy of pursuing, and that it has desirable consequences for disadvantaged students. Therefore, DE programs can serve as an access and equity-enhancing educational policy tool when implemented properly. From this point of view, it is no surprise why DE has experienced such aggressive growth. Nevertheless, the funding, eligibility, delivery, and rules of DE programs are heterogeneous throughout states around the country. Therefore, any estimation of the effects of DE on different student populations must be examined in context. Alternatively, knowledge of the demographic description of DE participants across the U.S. is more reasonably generalizable and can assay access efficiency.

Literature concerning the student characteristics that increase the likeliness a student participating in dual credit coursework is non-existing. There is, however, an analog to this paper but with emphasis on AP Economics participation (Scafidi, Clark, & Swinton, 2015). Scafidi et al found that minority students and those students from low socioeconomic family backgrounds as half as likely to enroll in advanced coursework than their counterparts. Once they control for prior achievement, the disparity in participation attenuates for low SES students. Another notable finding from the authors is that once accounting for prior academic achievement; there is Hispanic and Black student overrepresentation in AP Economics participation when compared to Whites. The paper by Scafidi et al. on AP course taking and the research presented herein coincide at several junctures. First, both AP and DE are forms of advanced coursework which aims to facilitate the high school to college transition. Second, both Scafidi et al and this research found that prior

academic achievement plays a strong role in the likeliness of participating in accelerated programs. Most importantly perhaps is the fact that prior achievement seems to diffuse the effect of the ‘a priori' characteristics of participants such as race/ethnicity and socioeconomic backgrounds. The latter two have consistently been found important when understanding the achievement gap. Lastly, a gap in the literature exists concerning the student-level determinants of DE participation. This study attempts to fill this gap and discusses the research and policy implications of it.

Chapter 3: Data and Methodology

THE HIGH SCHOOL LONGITUDINAL STUDY OF 2009

Background

The High School Longitudinal Study of 2009 (HSLS:09) is the most recent of five studies stemming from the Secondary Longitudinal Studies (SLS) program instituted by the National Center for Education Statistics (NCES)[2]. These studies seek to observe students at different stages of their educational career with emphasis on their secondary and postsecondary experiences. NCES (2015) states that once completed; the five longitudinal studies will describe student cohorts spanning from 1972 to 2025. Thus, providing useful data for "understanding the correlates of educational success in the United States" (p.2). These longitudinal studies have been utilized extensively for a broad range of education research questions, and their results can be generalized and inform public policy.

The HSLS:09 follows a cohort of more than 23,000 9th graders from 944 high schools. One focus of the HSLS:09 is to learn about the educational career trajectories undertaken by students –from their early high school years to their post-secondary years, to them entering the workforce, and beyond. The results from the HSLS:09 are planned to be published first with a base year results report followed by a series of consecutive questionnaire results and transcript collection waves. To date, the base year and two waves of data have been published. The base year contains information of the student while being a ninth grader. The results from the first follow-up questionnaire were released in the spring of 2012 and contained data from the same cohort when they should have been 11^{th-}grade students as well as data from their attending high schools. The most recent published wave as of this writing is the 2013 Update and High School Transcript. The latter was administered between June and December of 2013, at which point most students had completed high school and unless they had not dropped out. Furthermore, the 2013 update data collection focused on high school completion, dual credit course taking, college enrollment, and

---

2 Four of these study series have been completed: National Longitudinal Study of 1972, High School and Beyond (1980), National Education Longitudinal Study of 1988, and Education Longitudinal Study of 2002.

employment among other outcomes (Dalton, Ingels, Fritch, & Christopher, 2016). NCES currently has no predetermined timeline for future follow-ups but plans to follow the sample cohort students to age 30 at a minimum (Ingels & Dalton, 2013).

Sample Design

The HSLS:09 base year sample was selected utilizing a two-stage process. In the first stage of sampling, stratified random sampling identified 1,889 eligible schools. From these schools, 944 participated in the study resulting in a 56 percent unweighted response rate. In the second stage, a random selection of ninth grade students resulted in 25,206 eligible units or students from which a little more than 21,000 participated. The unweighted response rate of eligible student participants is 86 percent (Ingels et al., 2011). The sample population includes public, private and charter schools from across the 50 United States and the District of Columbia.

This study utilizes the restricted data set from the HSLS:09 thus allowing for the use of variables considered as "high risk" by the NCES and not publicly available (Ingels et al., 2011). These variables include but are not limited to race/ethnic subgroup, geographic location, transcript data, among other data excluded from the public data set. The variables utilized from this study are from data collected in the base year survey through the 2013 follow-up. All the analysis presented in this paper is weighted employing analytic weights contained in the HSLS:09 data set. The use of the analytic weights with the aid of statistical software helps to account for the study's complex survey design. Lastly, all estimations in this research paper employ robust standard errors.

Descriptive Statistics

All the analyses presented in this paper have been weighted utilizing the Student Longitudinal Analytic Weight (W3W1W2STU) computed by the NCES for analyses related to changes across the base year, first follow-up, and the 2013 update (Dalton, Ingels, & Fritch, 2015). The use of the longitudinal weight allows for generalization of the findings at a national level for

all high school students (Ingels et al., 2011). Table 1 presents selected student-level summary statistics from the dataset. The information is presented for two groups of students; students who did not take any dual enrollment courses and students who took any dual enrollment courses during high school. The data shown in Table 1 reveals some interesting information on DE participation by race/ethnicity. Overrepresentation of white students in DE programs is observed in the sample. Noticeably, while Black and Hispanic students are underrepresented in DE programs, Asian students are not. This finding is consistent with the fact that Asian students have higher participation rates in advanced coursework programs such as AP and IB than any other racial/ethnic group (Musu-Gillette et al., 2016).

Regarding DE participation by gender, females make up most of the students. This finding is consistent with the observed trend of higher college and advanced coursework participation rates by females compared to males (Handwerk, Tognatta, Coley, & Gitomer, 2008; Kena et al., 2016).

The socioeconomic status variable (SES) and the poverty level indicator in Table 1 serve as a tool for comparing DE participation by the student family background. Table 1 below indicates that the probability of observing a student living on or below the federal poverty line in the full sample is 19.6 percent compared to 13.7 percent in the sub-sample including DE participants only. The SES variable indicates a higher value for students who took dual credit compared to those who did not. The difference in the SES value is .23 standard deviations above the mean compared to DE participants.

As a measure of achievement, Table 1 includes ninth-grade (GPA09) and twelfth-grade (GPA12) grade point average variables. Prior achievement as measured by GPA09 shows that DE participants have on average a higher overall grade point by about half a point. The previous statistic is further corroborated when comparing the twelfth-grade GPA of both groups of students in Table 1. The achievement indicators presented show that students participating in DE coursework are, on average, high achieving with a GPA above three or its equivalent, a letter grade "A".

In 2013, 9.6 percent of students in the HSLS:09 sample had earned dual-enrollment credit with 3.1 percent earned in math and 1.9 percent in science (Dalton et al., 2015). These numbers suggest that at least half of DE coursework undertaken in the U.S. is in STEM-related subjects, which is encouraging.

Table 1: Descriptive Statistics

	All Students		DE Participants		Variable Value Range	
	Mean	Std. Dev	Mean	Std. Dev	Min	Max
White	0.516		0.635		0	1
Black	0.137		0.088		0	1
Hispanic	0.221		0.163		0	1
Asian	0.036		0.040		0	1
Other Race	0.090		0.070		0	1
Female	0.500		0.576	0.494	0	1
9th Grade GPA	2.550	0.941	3.082	0.747	0	4
12th Grade GPA	2.746	0.815	3.112	0.674	0	4
Socio-Economic Status	0.073	0.757	0.161	0.748	1.930	2.881
Poverty Level	0.196		0.137		0	1
City	0.319		0.272		0	1
Suburb	0.333		0.315		0	1
Town	0.118		0.134		0	1
Rural	0.230		0.279		0	1
	N=	16,040	N=	2,980		

Source: U.S Department of Education, Institute of Education Sciences, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09), First Follow-up and 2013 Update Restricted-Use File.

METHODOLOGY

Empirical Approach

To estimate the probability of a student enrolling in DE during high school a logistic modeling approach is employed. The logit model is an appropriate statistical tool when the

dependent variable is discrete. Logistic regression recurs to a cumulative logistic distribution thus constraining the predictors to values between one and zero (Pindyck & Rubinfeld, 1998). The dependent variable utilized herein is S3DUAL[3], a dichotomous variable equal to 1 if a student has taken any DE course work and equal to 0 if the student has not. The estimation coefficients are presented as odds ratios.

Naïve Logit Regression Model

Three models are presented in this paper to ascertain what student characteristics prevail among DE participants. The first model is a naïve regression[4] of DE participation which does not include a prior academic achievement control. The dependent variable is regressed by race/ethnicity, gender, and socioeconomic status adjusted by location.

$$\log\left(\frac{P[DE]}{1-P[DE]}\right) = \beta_0 + \beta_1 Female + \beta_2 Black + \beta_3 Hispanic + \beta_4 Asian + \beta_5 OtherRace + \beta_6 SES_U + \varepsilon \qquad (1)$$

The reference or omitted groups are white and male students for race/ethnicity and gender characteristics. The naïve model provides a baseline for the two subsequent models and serves for comparability of the alternative specifications.

Prior Achievement Logit Model

The second model estimated is an improvement from the first by accounting for prior academic achievement:

$$\log\left(\frac{P[DE]}{1-P[DE]}\right) = \gamma_0 + \gamma_1 Female + \gamma_2 Black + \gamma_3 Hispanic + \gamma_4 Asian + \gamma_5 OtherRace + \gamma_6 SES_U + \gamma_7 GPA09 + \upsilon \qquad (2)$$

---

3 Name recoded to "DE."

4 This model specification partially mimics the empirical approach by Scafidi (2015) and by extension, from the findings by Conger et al. (2009).

State Effects Logit Model

The last model adds a factor variable accounting serving as a control for each state in the United States:

$$\log\left(\frac{P[DE]}{1-P[DE]}\right) = \delta_0 + \delta_1 Female + \delta_2 Black + \delta_3 Hispanic + \delta_4 Asian + \delta_5 OtherRace + \delta_6 SES_U + \delta_7 GPA09 + \phi_i + \nu \quad (3)$$

The variable ϕ_i is a vector of dichotomous variables with values of zero and one for all 50 states not including the nation's capital. The rationale behind the state variable is that there are unobserved phenomena affecting the access and distribution of DE courses among states. These unobserved effects could be funding, program requirements, and legislation, among others.

Independent Variables

The final three models presented in the main body of this paper strives for parsimony in its models and overall approach. Sensitivity analysis performed in corroboration of the final models can be found in the Appendix portion of this paper. All independent variables were re-coded from composite variables included in the dataset. The NCES employs robust imputation methods across all its composite variables thus maintaining sample size and integrity[5].

Gender and Race

The models in this paper control for gender with a binary variable and the omitted group are males. Any estimated coefficient is interpreted with male students as the reference group in all three logistical models. A set of dichotomous variables is included in the data set controlling for six main racial/ethnic groups: White, African American, Hispanic, Asian, Pacific Islander and Native American. Given their small number and for the purposes of the estimations in Chapter 4, the latter two groups of races were combined into the single variable *OtherRace*.

[5] The imputation methods used in the HSLS:09 can be found in the data set's documentation file which is publicly available at http://nces.ed.gov/pubsearch.

Socioeconomic Status

Socioeconomic status (SES) is a measurement which primarily combines the income, education, and occupation of a family, household or individual (Scott & Marshall, 2009). Therefore, SES is a descriptor of social rank. The effects student-level and school-level SES on education attainment and academic achievement have been widely studied in the last sixty years (Chubb & Moe, 1991; Coleman & Department of Health USA, 1966; Palardy, 2008; Reardon, 2011; Sirin, 2005). Notably, Reardon (2011) asserts that the link between socioeconomic status and academic achievement has become stronger in recent decades; suggesting that the income achievement gap in the United States has widened, perhaps, in concert with income inequality. A student's SES could be logically viewed as part of the initial economic endowment provided to her. More affluent families often invest more intensively in their child's education. Activities such as exam preparation or tutoring are more accessible to certain income ranges. Furthermore, parents with higher SES are more likely to value education and may have larger expectations for their children. Thus, the use of an SES index is appropriate when exploring which student characteristics increase the likelihood of a student participating in DE.

NCES has included an SES index since the NLS:72 and has continuously improved the building method related to its construction in each consequent study for the SLS program[6]. These improvements in the SES variable account for social changes in household composition and dynamics such as parental roles and female labor participation (Ingels et al.,2015). The HSLS:09 includes two SES composite variables built upon three fundamental measures –family income, parent or guardian level of education, and parent or guardian occupation prestige. The first SES index (X1SES) was designed to be comparable to previous studies by the NCES. The second SES index (X1SES_U) is only different in that it contains a school location component[7]. The models and results presented in this paper will employ the X1SES_U variable as its SES control.

---

[6] The SES index variable design and methodologies are complex. Comprehensive information can be found in the Base Year Data File Documentation Appendix J.

[7] The location categories incorporated to the X1SES_U variable are: City, Suburb, Town, and Rural.

Academic Achievement

In the investigation of achievement gaps[8], controls for academic achievement are necessary. Particularly, when attempting to elucidate differences in outcomes among racial/ethnic and social groups. It is then pertinent for researchers to utilize the best available proxy for academic performance. In the context of advanced coursework, there is some evidence that accounting for prior academic achievement dissipates differences among racial groups (Conger, Long, & Iatarola, 2009; Scafidi et al., 2015).

The HSLS:09 contains a diverse selection of academic achievement variables. These variables include math scores, GPA[9], standardized test scores[10], and others. In selecting the appropriate achievement variable for this study, it was important to utilize a measure of achievement prior to the student's decision to participate in DE coursework. As mentioned at the beginning of this paper, DE enrollment can occur as early as the student's sophomore year but typically occurs during the Junior and Senior years of high school. Therefore, controlling for achievement before program participation is essential. Having access to the restricted data set made this task possible. The HSLS:09 includes a composite GPA variable for grades nine, eleven and twelve. The overall ninth grade student GPA is utilized to control for prior achievement in the estimations of the models developed in this paper.

State Effects

A state factor variable is employed in the third model presented to account for state heterogeneity. Each state has distinct requisites, policies, laws, and formats in the delivery of DE programs. For this reason, a state factor variable which creates binary variables for each state accounts for unobservable variation affecting the outcome variable DE.

---

[8] Although implicitly, this paper functions under the assumption that there is an achievement gap along race/ethnicity, gender, and socioeconomic characteristics.
[9] To include subject-specific, overall, and overall honors weighted GPA.
[10] PSAT, SAT, and ACT.

Chapter 5: Results

The three models' estimation results are shown in Table 2. The naïve model presents the finding that when not controlling for academic achievement, minority groups –apart from Asian students– are at a disadvantage or do not have sufficient access to DE coursework or programs. In the naïve model estimations, Black and Hispanic students are 44 and 30 percent less likely to be observed taking DE courses at a highly statistically significant level ($p<.001$). Furthermore, and in consonance with the descriptive statistics provided in the previous chapter, females are 53 percent more likely to take any dual credit class than their male counterparts. Socioeconomic status is also a highly statistically significant predictor of a student enrolling in DE coursework in the first model in Table 2.

Table 2: Models 1-3

	Naïve Model			Prior Achievement			State Effects		
Independent Variable	Odds Ratio		SE	Odds Ratio		SE	Odds Ratio		SE
Female	1.539	***	0.060	1.255	***	0.067	1.213	**	0.069
xblack	0.560	***	0.138	0.837		0.148	0.885		0.155
xhisp	0.703	***	0.100	0.909		0.112	0.861		0.109
xasian	0.846		0.148	0.646	**	0.155	0.790		0.161
xotherrace	0.672	***	0.103	0.786	*	0.110	0.838		0.116
x1ses_u	1.482	***	0.038	1.124	**	0.044	1.175	***	0.045
x3gpa09				2.233	***	0.048	2.380	***	0.051

Note: Reference groups are White and Male.
*p<.05 **p<.01 ***p<.001

The second or "Prior Achievement" model, produce noteworthy results as it relates to DE participation by race/ethnicity. Once controlling for prior achievement, the statistical significance of the race/ethnic control variables is lost at the $p<.05$ level. The prior achievement variable as accounted for by ninth grade GPA has a large odds ratio and is significant at the p<.001 level in the second model. Holding all other control variables constant, a student is over twice as likely to

take any college-level coursework for each unit increase in her grade point average. The findings from the second model illuminate the crucial importance of prior academic achievement in the context of DE enrollment. Moreover, the SES estimated coefficient becomes smaller once the previous ability of students is accounted for in the model. This probability decreases from 48 percent to 12 percent more likely to enroll in DE for an increase each standard deviation increase in SES. The gender variable is consistent in the previous model both in the magnitude of its coefficient and the robust standard errors.

The third model included a dichotomous variable for each state in the sample. As mentioned previously, this is to control for unobservable effects due to the heterogeneity of state programs across the country. After its estimation, the third model affirms the statistical significance found in the second model's SES and academic achievement coefficients. The strong influence that prior achievement and SES exert on the probability of participation may point out to a lack of access for low SES students as well as the average academic performing student. While it is expected to assume that a certain level of academic competency is needed for accelerated courses, the results indicate that even after holding academic ability constant, SES will play a major role in predicting DE participation. Furthermore, the third model's estimates suggest that being from a minority race/ethnic group is not a statistically significant predictor of DE enrollment. Although the race/ethnic point estimates may imply that DE may be a 'color blind' program, they should be interpreted with caution. Lastly, the finding that females are more likely to participate than males remains in the third model.

Model Diagnostics

Multicollinearity

The independent variables selected for the construction of the models in this paper have the potential to suffer from multicollinearity. As mentioned previously, the achievement gap is observed along certain student characteristics. For instance, a student with higher parental family social status will tend to perform better than a financially challenged student. Alternately, racial

minorities tend to have lower SES when compared to whites. Low family SES is in turn related to lower education attainment outcomes. The three models presented in this research control for these characteristics mentioned above. For this reason, multicollinearity is suspect. A Pearson correlation coefficient matrix is presented for all seven independent variables in Table 2.

Table 3: Correlation Coefficient Matrix

Correlation Coefficients

Variable	1	2	3	4	5	6	7
1 Female							
2 Black	-0.0064						
3 Hispanic	0.0003	-0.148					
4 Asian	-0.0032	-0.1003	-0.1321				
5 OtherRace	-0.0026	-0.1123	-0.1479	-0.1002			
6 SES	0.0013	-0.0904	-0.2559	0.1035	-0.016		
7 GPA	0.1854	-0.1543	-0.1429	0.1647	-0.0464	0.3919	
N=19,580							

The information presented in Table 3 indicate that the highest correlation among the independent variables is between ninth grade GPA and the socioeconomic status variable. Although not fatal, the correlation coefficient is positive. However, because the race/ethnicity variables are binary and the SES and GPA variables are continuous, the Pearson correlation coefficients may not be a valid test for collinearity. Thus, any correlation coefficients presented in Table 3 between a continuous variable and a dichotomous variable must not be relied upon. To test for multicollinearity, the STATA software program *collin* was executed on all independent variables excluding the state binary variables before the estimation of the models[11]. The results from this collinearity test are presented in Table 3. The Variance Inflation Factor (VIF) serves as a gauge of the inflation of the standard error due to collinearity. In fact, a VIF of 1 would indicate

[11] Although VIF calculations are usually obtained post-estimation, it is not a necessity given that collinearity is a characteristic of the predictor variables.

that all the variables tested are orthogonal to each other. A common benchmark is that any VIF of 10 or greater would be a cause of concern for collinearity.

Table 4: Collinearity Diagnostics

Variable	VIF	Tolerance
Female	1.02	0.9582
Black	1.05	0.9058
Hispanic	1.08	0.8507
Asian	1.03	0.9346
OtherRace	1.04	0.9328
SES	1.12	0.7954
GPA09	1.13	0.7796
Mean VIF	1.14	
N=19,580		

The VIF values presented in Table 4 do not include any value higher than 10, and the mean VIF is 1.14. Therefore, collinearity is not an issue for the independent variables selected.

Chapter 6: Conclusion

The three models presented in this paper aim to provide a snapshot of the student characteristics observed for DE coursework participants in the United States. It is important to note that the information collected by the HSLS:09 as it relates to DE is limited to identifying participation. Furthermore, the HSLS:09 DE variables do not offer any specific insights about the content, quality, or other relevant aspects of DE coursework delivery. Research about such insights are beyond the scope of this paper. Nevertheless, investigating the composition and the factors influencing DE participation provides policy makers a measure of their efforts in making DE available for any particular group or set of groups. As previously discussed, a concerted effort to provide access to DE to disadvantaged students is underway across the country. Because public funding and school districts are the main financiers of DE programs, it is then pertinent to understand if the equality of access goal is being achieved. The estimations presented in this paper leave three things clear: females participate in DE at higher rates than males; socioeconomic status is a strong predictor of DE participation; and that DE may predominantly be for high achieving students.

As mentioned above female students are overrepresented in DE coursework. This finding is parallel to that of Handwerk et al. (2008), which found consistently higher female student participation in a national cluster analysis of AP participation. The gender disparity in advanced coursework participation such as DE and AP should be of concern to policy makers as it suggests that the gender college gap is also present among high achieving students. Moreover, research about why female students tend to enroll more often in DE and AP programs could follow. Lastly, as already noted, STEM-related coursework comprises a substantive portion of DE programs. Therefore, the gender gap in STEM is potentially positively addressed by higher female DE participation.

A notable finding in the model estimations is the role of SES in DE participation. There is a dissonance between DE as a tool to close the achievement gap and what the models in this paper

indicate. If high SES families and students are mainly participating in DE coursework and programs, then there is the potential for unequal access. Furthermore, if it is the case that high income families are mainly taking advantage of DE coursework, it may be the case that low income schools and neighborhoods do not have equitable access to such coursework. Therefore, research controlling for school level characteristics could shed light about access to DE coursework in challenged schools. Because SES is closely related to achievement (Caldas & Bankston, 1997; Sewell and Sha, 1968), it is important for stakeholders to ensure access to low SES students and their schools. Additionally, considering that funding for these programs is predominantly public, there is a risk of subsidizing college education to those families and students that would otherwise attain a college degree. An efficient distribution of DE programs is one that benefits students regardless of their SES background. If distribution of DE coursework is not equitable, policy makers and stakeholders will be in contradiction of their own equity and access goals.

Detaching the relationship between race and SES is a Gordian Knot. The estimations presented in this paper suggest that, generally, and at a national and state level; race/ethnic background does not seem to hinder DE participation. However, the estimations in this paper suggest there is the possibility that more affluent schools and students will have higher DE participation rates. Therefore, it would be imprudent to assume total equity of access along racial lines knowing that race/ethnicity is closely related to SES. Consequently, the current state of DE program delivery and participation may not be effectively addressing the income achievement gap.

The descriptive statistics and model estimations suggest that high achieving students are predominantly participating in DE. Although the GPA requirements can be as low as 2.0 in some states, the participants' ninth grade GPA is on average a low A. The sample employed herein shows that GPA averages increase more over the high school years for non-participants than for DE students. In other words, GPA does not seem to change much during the high school years. Therefore, high achieving students will have a clear path to advanced coursework if they decide to take it. Investigating the effects of DE on GPA outcomes is another a research implication from this paper.

This paper set out to examine the characteristics of student populations participating in DE. It finds that higher social classes and high achievement students have the highest probability of taking part in these programs. This finding implies that equity of access to these programs may not be at an optimal level. As investment in DE programs continues to grow, policymakers should engage in cost-benefit analysis and contemplate the opportunity costs involved.

References

Allen, D., & Dadgar, M. (2012). Does dual enrollment increase students' success in college? Evidence from a quasi-experimental analysis of dual enrollment in new york city. *New Directions for Higher Education, 2012*(158), 11-19. doi:10.1002/he.20010

An, B. P. (2012). The impact of dual enrollment on college degree attainment do low-SES students benefit? *Educational Evaluation and Policy Analysis*, 0162373712461933.

Boswell, K. (2001). State policy and postsecondary enrollment options: Creating seamless systems. *New Directions for Community Colleges, 2001*(113), 7.

Card, D. (1999). The causal effect of education on earnings. *Handbook of Labor Economics, 3*, 1801-1863.

Cassidy, L., Keating, K., & Young, V. (2010). *Dual enrollment: Lessons learned on school-level implementation.* ().SRI International.

Ceroni, C. B. (2001). Poverty traps and human capital accumulation. *Economica, 68*(270), 203-219.

Chubb, J. E., & Moe, T. M. (1991). *British Journal of Sociology of Education, 12*(3), 381-396.

Coleman, J. S., & Department of Health USA. (1966). *Equality of educational opportunity* JSTOR.

Conger, D., Long, M. C., & Iatarola, P. (2009). Explaining race, poverty, and gender disparities in advanced course-taking. *Journal of Policy Analysis and Management, 28*(4), 555-576.

Dalton, B., Ingels, S. J., & Fritch, L. (2015). High school longitudinal study of 2009 (HSLS: 09). 2013 update and high school transcript study: A first look at fall 2009 ninth-graders in 2013. NCES 2015-037. *National Center for Education Statistics,*

Dalton, B., Ingels, S. J., Fritch, L., & Christopher, E. M. (2016). High school longitudinal study of 2009 (HSLS: 09).

Durlauf, S. N. (1996). A theory of persistent income inequality. *Journal of Economic Growth, 1*(1), 75-93.

Giani, M., Alexander, C., & Reyes, P. (2014). Exploring variation in the impact of dual-credit coursework on postsecondary outcomes: A quasi-experimental analysis of texas students. *The High School Journal,* (4), 200.

Handwerk, P., Tognatta, N., Coley, R. J., & Gitomer, D. H. (2008). Access to success: Patterns of advanced placement participation in US high schools. Policy information report. *Educational Testing Service,*

Haskell, R. E. (2016). The effects of dual-credit enrollment on underrepresented students: The Utah case. *International Journal of Economics and Finance, 8*(1), 144-165.

Heckman, J. J., Lochner, L. J., & Todd, P. E. (2003). *Fifty Years of Mincer Earnings Regressions,*

Hoffman, N., Vargas, J., & Santos, J. (2009). New directions for dual enrollment: Creating stronger pathways from high school through college. *New Directions for Community Colleges, 2009*(145), 43-58.

Hugo, E. B. (2001). Dual enrollment for underrepresented student populations. *New Directions for Community Colleges,* (113), 67-72.

Ingels, S. J., & Dalton, B. (2013). High school longitudinal study of 2009 (HSLS: 09) first follow-up: A first look at fall 2009 ninth-graders in 2012. NCES 2014-360. *National Center for Education Statistics,*

Ingels, S. J., Pratt, D. J., Herget, D. R., Burns, L. J., Dever, J. A., Ottem, R., . . . Leinwand, S. (2011). High school longitudinal study of 2009 (HSLS: 09): Base-year data file documentation. NCES 2011-328. *National Center for Education Statistics,*

Karp, M. M., Calcagno, J. C., Hughes, K. L., Jeong, D. W., & Bailey, T. R. (2007). The postsecondary achievement of participants in dual enrollment:" An analysis of student outcomes in two states.*" Community College Research Center, Columbia University,*

Katz, L. F., & Murphy, K. M. (1992). *Changes in relative wages, 1963-1987: Supply and demand factors* MIT Press.

Kena, G., Hussar, W., McFarland, J., de Brey, C., Musu-Gillette, L., Wang, X., . . . Diliberti, M. (2016). The condition of education 2016. NCES 2016-144. *National Center for Education Statistics,*

Lareau, A. (2011). *Unequal childhoods: Class, race, and family life* Univ of California Press.

Marken, S., Gray, L., & Lewis, L. (2013). Dual enrollment programs and courses for high school students at postsecondary institutions: 2010-11. First look. NCES 2013-002. *National Center for Education Statistics,*

Mincer, J. (1974). Schooling, experience, and earnings. *Explorations in Economic Research: Occasional Papers of the National Bureau of Economic Research, 1*(2), 404.

Musu-Gillette, L., Robinson, J., McFarland, J., KewalRamani, A., Zhang, A., & Wilkinson-Flicker, S. (2016). Status and trends in the education of racial and ethnic groups 2016. NCES 2016-007. *National Center for Education Statistics,*

Palardy, G. J. (2008). Differential school effects among low, middle, and high social class composition schools: A multiple group, multilevel latent growth curve analysis. *School Effectiveness and School Improvement, 19*(1), 21-49. doi:10.1080/09243450801936845

Pindyck, S., & Rubinfeld, L. (1998). Econometric models and economic forecasts.

Reardon, S. F. (2011). The widening academic achievement gap between the rich and the poor: New evidence and possible explanations. *Whither Opportunity*, 91-116.

Scafidi, B. P., Clark, C., & Swinton, J. R. (2015). Who takes advanced placement (AP)? *Eastern Economic Journal, 41*(3), 346-369.

Scott, J., & Marshall, G. (2009). *A dictionary of sociology* (3rd ed.) Oxford University Press.

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research, 75*(3), 417-453.

Swanson, J. (2007). Dual enrollment and advanced placement: Partners for student success. *Principal Leadership, 7*(7), 26-30.

Thomas, N., Marken, S., Gray, L., & Lewis, L. (2013). Dual credit and exam-based courses in US public high schools: 2010-11. First look. NCES 2013-001. *National Center for Education Statistics,*

Appendix

Figure 1: Logit Estimation Output - Naïve Model

Iteration 0:	log pseudolikelihood	-1903953.6	[pw=W3W1W2STU]
Iteration 1:	log pseudolikelihood	-1841555.9	
Iteration 2:	log pseudolikelihood	-1840236.1	
Iteration 3:	log pseudolikelihood	-1840235.1	
Iteration 4:	log pseudolikelihood	-1840235.1	

Logistic regression	Number of obs	15,100
	Wald chi2(6)	238.47
	Prob > chi2	0
Log pseudolikelihood = -1840235.1	Pseudo R2	0.0335

Dependent **DE** Independent	Coef.	Robust Std. Error	z	P>z	[95% Conf.	Interval]
Female	0.4313608	0.06002154	7.16	0.000	.3133408	0.5493808
Black	-0.5799064	0.1382662	-4.19	0.000	-.8509032	-0.3089097
Hisp	-0.352381	0.0999725	-3.52	0.000	-.5483235	-0.1564385
Asian	-0.1668687	0.1479968	-1.13	0.260	-.456937	0.1231997
OtherRace	-0.3976117	0.1030963	-3.86	0.000	-.5996767	-0.1955468
SES_U	0.3935156	0.0378146	10.41	0.000	.3194003	0.467631
Cons	-1.509267	0.0485246	-31.1	0.000	-1.604374	-1.414161

Figure 2: Logit Estimation Output - Prior Achievement

Iteration 0:	log pseudolikelihood	-1768795	[pw=W3W1W2STU]
Iteration 1:	log pseudolikelihood	-1626707.1	
Iteration 2:	log pseudolikelihood	-1617683.2	
Iteration 3:	log pseudolikelihood	-1617672.2	
Iteration 4:	log pseudolikelihood	-1617672.2	

Logistic regression	Number of obs	14,020
	Wald chi2(7)	474.56
	Prob > chi2	0
Log pseudolikelihood = -1617672.2	Pseudo R2	0.0854

Dependent **DE** Independent	Coef.	Robust Std. Error	z	P>z	[95% Conf.	Interval]
Female	0.2270332	0.0674466	3.37	0.001	.0948404	0.359226
Black	-0.1779398	0.1481015	-1.2	0.230	-.4682133	0.1123338
Hisp	-0.09525	0.1115406	-0.85	0.393	-.3138655	0.1233656
Asian	-0.4377112	0.154642	-2.83	0.005	-.7408039	-0.1346185
OtherRace	-0.2411072	0.1100956	-2.19	0.029	-.4568906	-0.0253238
SES_U	0.1171119	0.043708	2.68	0.007	.0314458	0.202778
GPA09	0.8032729	0.0484122	16.59	0.000	.7083867	0.8981592
Cons	-3.711691	0.1443786	-25.71	0.000	-3.994667	-3.428714

Figure 3: State Effects

note: 15.X1STATE != 0 predicts failure perfectly
15.X1STATE dropped and 17 obs not used

Iteration 0: log pseudolikelihood = -1768429.1 [pw=W3W1W2STU]
Iteration 1: log pseudolikelihood = -1533315.1
Iteration 2: log pseudolikelihood = -1508805.7
Iteration 3: log pseudolikelihood = -1508401.6
Iteration 4: log pseudolikelihood = -1508369.1
Iteration 5: log pseudolikelihood = -1508368.6
Iteration 6: log pseudolikelihood = -1508368.6

Logistic regression			
	Number of obs	=	14,000
	Wald chi2(55)	=	773.91
	Prob > chi2	=	0
Log pseudolikelihood = -1508368.6	Pseudo R2	=	0.1471

Dependent **DE** Independent	Coef.	Robust Std. Error	z	P>z	[95% Conf.	Interval]
Female	0.1932788	0.0691547	2.79	0.005	0.0577382	0.3288195
Black	-0.1217707	0.1546524	-0.79	0.431	-0.4248838	0.1813424
Hisp	-0.1499797	0.1086176	-1.38	0.167	-0.3628662	0.0629069
Asian	-0.2353952	0.1612077	-1.46	0.144	-0.5513564	0.0805661
OtherRace	-0.1770342	0.1163427	-1.52	0.128	-0.4050618	0.0509934
SES_U	0.1613946	0.0449121	3.59	0	0.0733686	0.2494206
GPA09	0.8672288	0.0508047	17.07	0	0.7676534	0.9668043
X1STATE						
Alaska	0.6680128	0.4516336	1.48	0.139	-0.2171727	1.553198
Arizona	1.351096	0.2855108	4.73	0	0.7915048	1.910687
Arkansas	1.756137	0.348535	5.04	0	1.073021	2.439253
California	0.2946196	0.2710077	1.09	0.277	-0.2365457	0.8257849
Colorado	0.8118413	0.2946717	2.76	0.006	0.2342954	1.389387
Connecticut	-0.1793348	0.5425581	-0.33	0.741	-1.242729	0.8840595
Delaware	-2.964144	1.031424	-2.87	0.004	-4.985699	-0.9425896
Florida	1.640162	0.2487481	6.59	0	1.152625	2.1277
Georgia	0.1553828	0.2732977	0.57	0.57	-0.3802709	0.6910364
Hawaii	0	(empty)				
Idaho	1.918032	0.6847422	2.8	0.005	0.5759618	3.260102
Illinois	1.235408	0.2516376	4.91	0	0.7422074	1.728609
Indiana	1.768552	0.2569587	6.88	0	1.264922	2.272182
Iowa	1.988737	0.3385707	5.87	0	1.325151	2.652324
Kansas	0.9942417	0.3219349	3.09	0.002	0.363261	1.625222
Kentucky	1.232594	0.2859808	4.31	0	0.672082	1.793106
Louisiana	1.057175	0.3114883	3.39	0.001	0.4466693	1.667681
Maine	-2.038162	1.081684	-1.88	0.06	-4.158224	0.0819004
Maryland	0.1334008	0.3439473	0.39	0.698	-0.5407235	0.8075252
Massachusetts	-0.0757214	0.6061517	-0.12	0.901	-1.263757	1.112314
Michigan	0.5361672	0.2448023	2.19	0.029	0.0563635	1.015971
Minnesota	0.7851468	0.2763053	2.84	0.004	0.2435984	1.326695
Mississippi	-0.2506663	0.4635783	-0.54	0.589	-1.159263	0.6579305
Missouri	1.3827	0.2743073	5.04	0	0.845067	1.920332
Montana	-0.0251773	0.6276692	-0.04	0.968	-1.255386	1.205032
Nebraska	1.053914	0.4348915	2.42	0.015	0.2015425	1.906286
Nevada	0.3833943	0.5775734	0.66	0.507	-0.7486288	1.515417
New Hampshire	0.8454897	0.4411344	1.92	0.055	-0.0191178	1.710097
New Jersey	0.2051297	0.3056151	0.67	0.502	-0.3938649	0.8041243
New Mexico	2.197852	0.4899226	4.49	0	1.237622	3.158083
New York	1.715427	0.2442738	7.02	0	1.236659	2.194195
North Carolina	0.0262651	0.2644551	0.1	0.921	-0.4920573	0.5445875
North Dakota	2.640184	0.4513126	5.85	0	1.755627	3.52474
Ohio	0.6704762	0.2582774	2.6	0.009	0.1642617	1.176691
Oklahoma	1.2364	0.3381245	3.66	0	0.5736883	1.899112
Oregon	1.463449	0.3388481	4.32	0	0.7993192	2.127579
Pennsylvania	0.2633016	0.242771	1.08	0.278	-0.2125207	0.7391239
Rhode Island	1.690016	0.5666399	2.98	0.003	0.5794217	2.800609
South Carolina	1.091952	0.3401258	3.21	0.001	0.4253177	1.758586
South Dakota	-0.808195	1.10284	-0.73	0.464	-2.969722	1.353332
Tennessee	1.094581	0.2353132	4.65	0	0.6333753	1.555786
Texas	1.845733	0.2434143	7.58	0	1.368649	2.322816
Utah	1.549861	0.6202093	2.5	0.012	0.334273	2.765449
Vermont	1.229654	0.489	2.51	0.012	0.2712312	2.188076
Virginia	1.32198	0.2741592	4.82	0	0.7846374	1.859322
Washington	1.020523	0.2473275	4.13	0	0.5357704	1.505277
West Virginia	0.6028797	0.4055977	1.49	0.137	-0.1920772	1.397837
Wisconsin	0.0635913	0.3506431	0.18	0.856	-0.6236565	0.7508391
Wyoming	0.9371339	0.4694578	2	0.046	0.0170134	1.857254
_cons	-4.866615	0.2599215	-18.72	0	-5.376052	-4.357179

Figure 4: Alternative Naïve Model Specification

```
Iteration 0:  log pseudolikelihood            -1645910.5 [pw=W3W1W2STU]
Iteration 1:  log pseudolikelihood            -1591394.7
Iteration 2:  log pseudolikelihood            -1590313.8
Iteration 3:  log pseudolikelihood            -1590313.1
Iteration 4:  log pseudolikelihood            -1590313.1
```

Logistic regression	Number of obs	=	12,710
	Wald chi2(10)	=	189.77
	Prob > chi2	=	0
Log pseudolikelihood = -1590313.1	Pseudo R2	=	0.0338

Dependent **DE** Independent	Coef.	Robust Std. Error	z	P>z	[95% Conf.	Interval]
Female	0.4558068	0.0643455	7.08	0.000	.3296921	0.5819216
Black	-0.5715991	0.1515072	-3.77	0.000	-.8685477	-0.2746504
Hisp	-0.3077493	0.1052227	-2.92	0.003	-.513982	-0.1015166
Asian	-0.0343032	0.1694619	-0.2	0.840	-.3664424	0.2978359
OtherRace	-0.3618694	0.1105901	-3.27	0.001	-.5786221	-0.1451168
ParentalEdu	0.1533763	0.0256393	5.98	0.000	.1031242	0.2036283
FamilyIncome	0.0198516	0.0126067	1.57	0.115	-.004857	0.0445603
City	-0.3674868	0.089097	-4.12	0.000	-.5421136	-0.1928599
Suburb	-0.3853103	0.0777012	-4.96	0.000	-.5376018	-0.2330189
Town	-0.054481	0.1023286	-0.53	0.594	-.2550415	0.1460794
Cons	-1.793366	0.1001327	-17.91	0.000	-1.989623	-1.59711

Figure 5: Alternative Prior Achievement Model

```
Iteration 0:  log pseudolikelihood    -1530443.5 [pw=W3W1W2STU]
Iteration 1:  log pseudolikelihood    -1411732.7
Iteration 2:  log pseudolikelihood      -1404994
Iteration 3:  log pseudolikelihood    -1404968.5
Iteration 4:  log pseudolikelihood    -1404968.5
```

Logistic regression	Number of obs	=	11,820
	Wald chi2(11)	=	368.92
	Prob > chi2	=	0
Log pseudolikelihood = -1404968.5	Pseudo R2	=	0.082

Dependent **DE** Independent	Coef.	Robust Std. Error	z	P>z	[95% Conf.	Interval]
Female	0.256237	0.0720964	3.55	0.000	.1149306	0.3975434
Black	-0.1659242	0.1612242	-1.03	0.303	-.4819178	0.1500693
Hisp	-0.0384772	0.1173466	-0.33	0.743	-.2684723	0.1915178
Asian	-0.2750015	0.1760933	-1.56	0.118	-.6201381	0.0701351
OtherRace	-0.2127442	0.1166433	-1.82	0.068	-.4413609	0.0158725
ParentalEdu	0.0618154	0.0280034	2.21	0.027	.0069298	0.116701
FamilyIncome	-0.0088666	0.014078	-0.63	0.529	-.0364589	0.0187258
City	-0.289816	0.0969307	-2.99	0.003	-.4797966	-0.0998353
Suburb	-0.3191645	0.0829619	-3.85	0.000	-.4817669	-0.1565621
Town	0.0465615	0.1067431	0.44	0.663	-.1626511	0.2557741
GPA09	0.771895	0.0519264	14.87	0.000	.6701212	0.8736688
Cons	-3.592868	0.161162	-22.29	0.000	-3.90874	-3.276997

Figure 6: Alternative State Effects Model

```
note: 15.X1STATE != 0 predicts failure perfectly
15.X1STATE dropped and 12 obs not used

note: 23.X1STATE != 0 predicts failure perfectly
23.X1STATE dropped and 18 obs not used

Iteration 0:   log pseudolikelihood = -1528821.5
Iteration 1:   log pseudolikelihood = -1322723.7
Iteration 2:   log pseudolikelihood = -1302580.1
Iteration 3:   log pseudolikelihood = -1302279.4
Iteration 4:   log pseudolikelihood = -1302257.8
Iteration 5:   log pseudolikelihood = -1302257.6
Iteration 6:   log pseudolikelihood = -1302257.6

Logistic regression                                    Number of obs          11,790
                                                       Wald chi2(58)          688.33
                                                       Prob > chi2                 0
Log pseudolikelihood = -1302257.6                      Pseudo R2              0.1482
```

Dependent **DE** Independent	Coef.	Robust Std. Error	z	P>z	[95% Conf.	Interval]
xfemale	0.2092145	0.0741082	2.82	0.005	0.0639651	0.3544639
xblack	-0.0762122	0.1694294	-0.45	0.653	-0.4082877	0.2558634
xhisp	-0.0695624	0.1142898	-0.61	0.543	-0.2935663	0.1544415
xasian	-0.0550203	0.1873488	-0.29	0.769	-0.4222171	0.3121765
xotherrace	-0.1550487	0.1229456	-1.26	0.207	-0.3960177	0.0859202
paredu	0.0737068	0.0285616	2.58	0.01	0.017727	0.1296865
x1faminc	0.0048302	0.0145465	0.33	0.74	-0.0236804	0.0333408
city	-0.3041218	0.1002817	-3.03	0.002	-0.5006704	-0.1075732
suburb	-0.4255263	0.0892556	-4.77	0	-0.600464	-0.2505886
town	0.1016884	0.1123832	0.9	0.366	-0.1185786	0.3219554
x3gpa09	0.8323436	0.0541425	15.37	0	0.7262261	0.938461
X1STATE						
Alaska	0.8875725	0.4747975	1.87	0.062	-0.0430134	1.818159
Arizona	1.579329	0.2965535	5.33	0	0.9980948	2.160563
Arkansas	1.850599	0.3784176	4.89	0	1.108914	2.592284
California	0.3905264	0.2852563	1.37	0.171	-0.1685657	0.9496185
Colorado	0.9909352	0.3102627	3.19	0.001	0.3828314	1.599039
Connecticut	-0.1993746	0.5727617	-0.35	0.728	-1.321967	0.9232177
Delaware	-2.528718	1.033374	-2.45	0.014	-4.554094	-0.5033423
Florida	1.861349	0.2590527	7.19	0	1.353615	2.369083
Georgia	0.0798056	0.2871701	0.28	0.781	-0.4830375	0.6426487
Hawaii	0	(empty)				
Idaho	2.385368	0.7913703	3.01	0.003	0.8343105	3.936425
Illinois	1.336402	0.2655804	5.03	0	0.8158744	1.85693
Indiana	1.882281	0.2669249	7.05	0	1.359118	2.405444
Iowa	1.97038	0.3640925	5.41	0	1.256772	2.683988
Kansas	1.413173	0.3365531	4.2	0	0.7535408	2.072805
Kentucky	1.223379	0.297916	4.11	0	0.6394744	1.807284
Louisiana	0.9522116	0.3211888	2.96	0.003	0.3226932	1.58173
Maine	0	(empty)				
Maryland	0.523696	0.3551256	1.47	0.14	-0.1723374	1.219729
Massachusetts	-0.0354938	0.7613451	-0.05	0.963	-1.527703	1.456715
Michigan	0.6584605	0.2555801	2.58	0.01	0.1575327	1.159388
Minnesota	0.7636435	0.2917926	2.62	0.009	0.1917404	1.335547
Mississippi	-0.3997397	0.4904897	-0.81	0.415	-1.361082	0.5616025
Missouri	1.717397	0.2807769	6.12	0	1.167085	2.26771
Montana	0.0448401	0.6699611	0.07	0.947	-1.26826	1.35794
Nebraska	1.034997	0.4237476	2.44	0.015	0.2044668	1.865527
Nevada	0.4093881	0.6150805	0.67	0.506	-0.7961474	1.614924
New Hampshire	1.034078	0.4620832	2.24	0.025	0.1284118	1.939745
New Jersey	0.4530447	0.3222591	1.41	0.16	-0.1785715	1.084661
New Mexico	1.940284	0.5894985	3.29	0.001	0.7848885	3.09568
New York	1.880502	0.2570911	7.31	0	1.376612	2.384391
North Carolina	-0.018335	0.2671691	-0.07	0.945	-0.5419768	0.5053069
North Dakota	2.786632	0.4858577	5.74	0	1.834369	3.738896
Ohio	0.8472595	0.269824	3.14	0.002	0.3184143	1.376105
Oklahoma	1.22407	0.3646946	3.36	0.001	0.5092821	1.938859
Oregon	1.779197	0.3629738	4.9	0	1.067781	2.490612
Pennsylvania	0.4386313	0.2528434	1.73	0.083	-0.0569326	0.9341952
Rhode Island	1.629486	0.7372581	2.21	0.027	0.184487	3.074485
South Carolina	1.31133	0.3471295	3.78	0	0.6309688	1.991691
South Dakota	-0.528524	1.111036	-0.48	0.634	-2.706114	1.649066
Tennessee	1.062912	0.2446491	4.34	0	0.5834083	1.542415
Texas	1.916085	0.2543172	7.53	0	1.417632	2.414537
Utah	1.740557	0.7041317	2.47	0.013	0.3604838	3.120629
Vermont	1.026705	0.5299899	1.94	0.053	-0.0120563	2.065466
Virginia	1.399825	0.2861388	4.89	0	0.8390032	1.960647
Washington	1.119386	0.2587154	4.33	0	0.6123126	1.626458
West Virginia	0.7013805	0.4227706	1.66	0.097	-0.1272346	1.529996
Wisconsin	-0.0006664	0.3981074	0	0.999	-0.7809426	0.7796098
Wyoming	0.4806264	0.5126021	0.94	0.348	-0.5240554	1.485308
_cons	-4.911502	0.2734935	-17.96	0	-5.44754	-4.375465

Vita

Luis Eduardo graduated from the University of Texas at El Paso with a BBA in Economics in 2013. After working in the private sector for two years, he joined the MS in Economics program at his alma mater. In the summer of 2015, he obtained a Graduate Research Assistant position at the Hunt Institute for Global Competitiveness where he collaborated on research projects related to the Paso del Norte region. In the summer of 2016, he joined the College of Education also as a Research Assistant working under the tutelage of Dr. Stephen Kotok. During this time, he collaborated on educational research projects and co-authored the research paper "A Demographic Paradox: How Public School Students in New Orleans Have Become More Racially Integrated and Isolated since Hurricane Katrina" in the Education and Urban Society academic journal. He is currently considering to further advance his academic research experience in Educational Policy issues by pursuing a doctorate or joining an educational research organization.

Email Address: riveraluiseduardo@gmail.com

This thesis was typed by Luis Eduardo Rivera.