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Choices and Tradeoffs on the Path to a Bachelor's Degree: Essays on Academic Match, College Affordability, and Student Engagement

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Abstract

Lackluster BA completion rates have made it clear that improving postsecondary outcomes in the U.S. is not simply a matter of raising college enrollment rates. In addition to increasing the number of people who attend college, it is also important to increase the number of people who graduate. Over the years, scholars have identified many factors that help and hinder students as they make their way through college. One of these factors, and the focus of this three-study dissertation, is college choice. By college choice, I mean students' decisions about where to attend college. One way to think about college choice is to think about it in terms of academic match. Academic match refers to the alignment between a student's academic qualifications and the selectivity of the college they attend. Students "match" when they attend colleges that are well-aligned with their academic qualifications. Conversely, they "undermatch" when they attend colleges that are less selective than we might expect, and they "overmatch" when they attend colleges that are more selective than we might expect.

A consistent finding from the existing research on academic match is that students who match or overmatch are more likely to complete a BA than those who undermatch. Little is known, however, about whether this association has changed over time. In Study 1, I use nationally representative data from three cohorts of first-time college students—students who began college in 1995, 2003, and 2011—to examine this question. Findings from this descriptive study show that, in some ways, the association between academic match and BA completion has remained stable over time; across all three cohorts, matched and overmatched students are more likely to graduate than undermatched students. In other ways, however, the association may be evolving; overall, overmatched students' odds of graduation have increased over time, while

matched and undermatched students' have not. Study 1 highlights the continued importance of programs and interventions that seek to improve BA completion rates by reducing the prevalence of undermatch. By connecting these findings to broader trends in higher education, it also provides some working hypotheses for *why* academic match continues to be a strong predictor of student success. This sets the stage for future, hypothesis-testing research with additional implications for policy and practice.

In Study 2, I contribute to the literature on college choice by evaluating the plausibility of the "cost hypothesis," as it relates to college proximity and college choice. Existing research has found that college proximity plays an important role in the college choice process. While it is true that some students are eager to attend colleges that are far from their hometowns, the more common scenario is for students to attend colleges that are close to home. Many scholars have argued that this is because it can be more costly to attend a far-away college. I refer to this as the "cost hypothesis." If it is more costly to attend a far-away college, then people who live in areas where colleges are few and far between—areas with low geographic access to higher education—may find it especially challenging to pay for college, as they have no choice but to attend colleges that are relatively far away. Study 2 assesses the plausibility of this line of reasoning by examining the association between geographic access to higher education, distance traveled to college, and college costs, as indicated by student debt. Using data from the High School Longitudinal Study of 2009, I find that people with lower levels of geographic access tend to travel longer distances to attend college. In addition, I find that people who travel longer distances tend to accumulate more student debt. Finally, I find suggestive evidence that people with lower levels of geographic access tend to accumulate more student debt. These descriptive insights pave the way for future research on this topic. Additional research in this area could be one of the keys to understanding, and ultimately remedying, geographic inequalities in postsecondary outcomes.

In Study 3, I contribute to the literature on college choice by investigating whether, for some students, there may be important drawbacks to attending a match college or, more generally, a more selective college. Several studies have highlighted the fact that, for students from low-income, first-generation, and minoritized backgrounds, selective colleges can be socially isolating and difficult to navigate. Given this, some have wondered whether *less* selective colleges may offer more welcoming and engaging environments for students from these backgrounds. Study 3 uses data from the 2012/17 Beginning Postsecondary Students Longitudinal Study to examine whether this might be the case. Specifically, this descriptive study examines the association between college selectivity and affective engagement (feeling socially and emotionally connected to school), as well as the association between college selectivity and behavioral engagement (engaging in schooling-related activities). Findings show that students from a wide range of backgrounds report higher levels of affective and behavioral engagement at more selective, as opposed to less selective, colleges. This pattern is robust to several potential confounding factors, including college type, college size, and students' pre-college academic qualifications. However, although the association between selectivity and affective engagement is positive for most subgroups, it is relatively flat for Black students. Overall, Study 3 lends additional support to the argument that selective colleges, though far from perfect, have important advantages over their less selective counterparts. This study has implications for ongoing debates about college choice, including debates about the extent to which prospective college students should prioritize things like selectivity and prestige during the college search process. That said, more research is needed to fully understand the link between college selectivity and student engagement, as well as the link between college selectivity and other indicators of student wellbeing.

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Introduction

In the United States, higher education offers a critical pathway for social and economic mobility (Chetty et al., 2017; Hout, 1988; Torche, 2011). Recognizing this fact, policymakers and practitioners have worked for decades to expand access to higher education. They have built new colleges, established a financial aid system, and worked to cultivate a culture of "college for all" (Goldrick-Rab, 2017; Labaree, 2017; Rosenbaum, 2004). Today, roughly 70 percent of high school graduates enroll in college immediately after high school, and roughly 90 percent enroll within a decade of completing high school (Lauff et al., 2018; National Center for Educational Statistics, 2020). The vast majority of these students—over 80 percent—aspire to earn a bachelor's degree (BA) or higher (Pretlow, 2020, p. 12). However, less than 40 percent do so within six years of starting college (Pretlow, 2020, p. 6). Moreover, despite efforts to make higher education accessible to all, BA attainment rates remain highly stratified by socioeconomic status and race/ethnicity (Cahalan et al., 2021; Ma et al., 2019).

Lackluster degree completion rates and persistent inequalities have made it clear that improving postsecondary outcomes is not just a matter of raising college enrollment rates. In addition to increasing enrollment rates, we must also increase completion rates (Kelly & Schneider, 2012; Lederman, 2010; McNair et al., 2016; Mehaffy, 2018). One way to increase college completion rates is to focus on associate degrees and certificates. However, the most common degree, the degree that most students desire, and the degree with the highest and most consistent rewards is the bachelor's degree (Barrow & Malamud, 2015; Goldin & Katz, 2010; Hout, 1988; Torche, 2011). Thus, in addition to focusing on associate degrees and certificates, it is also important for scholars, policymakers, and practitioners to focus on increasing BA attainment rates and narrowing BA attainment gaps.

Over the years, scholars have identified many factors that help and hinder students as they make their way towards a bachelor's degree (Adelman, 2006; Bound et al., 2010; Bowen et al., 2009; Dynarski, 2003; N. W. Hillman et al., 2014). One of these factors, and the focus of this three-study dissertation, is *college choice*. By college choice, I mean students' decisions about where to attend college. Existing research on college choice has shown that, all else being equal, students who start their college careers at four-year institutions are more likely to complete a BA than those who start at two-year institutions (Lockwood Reynolds, 2012; Long & Kurlaender, 2009). Moreover, among four-year enrollees, those who attend more selective colleges are more likely to graduate than those who attend less selective colleges (Bowen et al., 2009; Dillon & Smith, 2020; Ovink et al., 2018; Shamsuddin, 2016). These patterns are consistent across numerous correlational and causal studies, and they help to explain bachelor's degree attainment disparities by socioeconomic status (SES) and race/ethnicity. This is because students from lower SES backgrounds, many of whom are from historically marginalized racial/ethnic groups, are less likely than their higher SES counterparts to enroll in four-year and more selective four-year colleges, all else being equal (Bastedo & Jaquette, 2011; Smith et al., 2013).

One way to think about college choice is to think about it in terms of academic match (Bastedo & Flaster, 2014; Roderick et al., 2011; Rodriguez, 2015). Academic match refers to the alignment between a student's academic qualifications and the selectivity of the college they attend. Students "match" when they attend colleges that are well-aligned with their academic qualifications. Conversely, they "undermatch" when they attend colleges that are less selective than we might expect, and they "overmatch" when they attend colleges that are more selective than we might expect. Many studies have shown that, for a variety of reasons, students who match or overmatch are more likely to complete a BA than those who undermatch (Bowen et al., 2009; Dillon & Smith, 2020; Ovink et al., 2018; Roderick et al., 2011). However, most of this research focuses on students who attended college in the 1990s or early 2000s. Since then, many important changes have occurred in higher education—changes which may have altered the association between academic match and degree completion. Thus, we are left to wonder, is academic match still an important predictor of BA completion? Moreover, is reducing the prevalence of undermatch still a viable strategy for improving BA completion rates?

In Study 1 of this dissertation, I use nationally representative data from three cohorts of first-time college students—students who began college in 1995, 2003, and 2011—to examine these questions. These data come from three separate administrations of the Beginning Postsecondary Students Longitudinal Study from the National Center for Education Statistics (NCES). Using a combination of descriptive statistics, logistic regression, and regression decomposition, I find that, in some ways, the association between academic match and BA completion has remained stable over time. Indeed, looking across all three cohorts, students who match or overmatch are more likely to complete a BA than those who undermatch, net of academic qualifications and demographic characteristics. In other ways, however, the association between academic match and BA completion has changed over time. Specifically, I find that overmatched students' odds of graduation have increased over time, while matched and undermatched students' have not. This study makes several contributions to the literature on college choice. Importantly, it shows that academic match continues to be an important predictor of student success in higher education, and that it may even be growing in significance over time. This highlights the continued importance of programs and interventions that seek to reduce both the prevalence and significance of undermatch, particularly for students from low-income, first-generation, and rural backgrounds. Study 1 also provides some working hypotheses for *why* academic match continues to be a strong predictor of BA completion. This sets the stage for future, hypothesis-testing research with additional implications for policy and practice.

Much of the research on college choice, including Study 1, offers support for the idea that students who attend match colleges are more likely to complete a BA than students who attend undermatch colleges. However, given the rising cost of college and growing concerns about student debt (Corkery & Cowley, 2017; Gicheva, 2016; Goldrick-Rab, 2017; Rothstein & Rouse, 2011; Zaloom, 2019), one must consider the financial tradeoffs that might accompany the decision to attend such a college. In other words, is it more expensive to attend a match college? Using data from several national sources, Howell and Pender (2016) shed some light on this question. They find that, on average, college costs for matched students tend to be higher than they are for undermatched students. Nevertheless, the authors conclude that the benefits of attending a match college, in terms of degree completion and employment outcomes, will outweigh the costs for most students.

Something that Howell and Pender do not address in their study is the fact that geographic access to match colleges, and to colleges in general, varies widely in the U.S. (N. W. Hillman, 2016; N. Hillman & Weichman, 2016; Turley, 2009). That is, some students live within a few miles of a match college, while others live hundreds of miles away. Many scholars have argued that distance-related costs may make it expensive to attend a far-away college than a nearby one (Briscoe & De Oliver, 2006; Card, 1995; Dillon & Smith, 2017; Do, 2004; Griffith & Rothstein, 2009; Rhodes, 2021; Spiess & Wrohlich, 2010; Turley, 2009). If this is the case, then the cost of attending a match college may be especially high for students from geographically isolated areas. This could erode some of the benefits that are associated with attending a such a college. It may also help to explain why students who live farther away from match colleges are more likely to undermatch and, consequently, less likely to earn a BA (Dillon & Smith, 2017; Ovink et al., 2018). Still, despite the long-recognized importance of college affordability in higher education policy discussions, there has been little empirical research on the association between geographic access and college costs.

In Study 2, I delve into this issue by examining the association between geographic access, distance traveled, and college costs, as indicated by student debt. The data for this study come from the High School Longitudinal Study of 2009, another nationally representative survey from NCES. Using a combination of descriptive statistics and multivariate regression models, I find that people with lower levels of geographic access to higher education tend to travel longer distances to attend college. In addition, I find that people who travel longer distances tend to accumulate more student debt. Finally, I find suggestive evidence that people with lower levels of geographic access tend to accumulate more student debt. This study contributes to the literature on geographic inequality in higher education by investigating whether geographic access is associated with student debt. It also contributes to the literature on college choice by assessing the plausibility of the "cost hypothesis," as it relates to geographic access and college choice. These descriptive insights pave the way for future research on this topic. Additional research in this area could be one of the keys to understanding, and ultimately remedying, geographic inequalities in postsecondary outcomes.

Financial considerations aside, there may be other tradeoffs that are associated with attending a match college or, more generally, a more selective college. Indeed, several studies have shown that, for students from low-income, first-generation, and minoritized backgrounds, selective colleges can be socially isolating and difficult to navigate (Armstrong & Hamilton, 2013; Jack, 2019; S. E. Johnson et al., 2011). This raises an important but unanswered question: when students from low-income, first-generation, and minoritized backgrounds attend less selective colleges—colleges with more diverse student bodies, but fewer financial resources—do they have a more positive college experience?

In Study 3, I use data from the 2012/17 Beginning Postsecondary Students Longitudinal Study to examine whether this might be the case. Specifically, I ask, is there an association between college selectivity and student engagement, and does this association vary by race/ethnicity and socioeconomic status? Following Ackert (2018), I examine two dimensions of student engagement: affective engagement (feeling emotionally and socially connected to school) and behavioral engagement (engaging in schooling-related activities). Using a combination of descriptive statistics and multivariate regression models, I find that students from a wide range of backgrounds report higher levels of engagement at more selective, as opposed to less selective, colleges. This pattern is robust to several potential confounding factors, including college type, college size, and students' pre-college academic qualifications. However, although the association between selectivity and affective engagement is positive for most subgroups, it is relatively flat for Black students. Overall, this study lends additional support to the argument that selective colleges, though far from perfect, have important advantages over their less selective counterparts. This study has implications for ongoing debates about college choice, including debates about the extent to which prospective college students should prioritize things like selectivity and prestige during the college search process. That said, more research is needed to fully understand the link between college selectivity and student engagement, as well as the link between college selectivity and other indicators of student wellbeing.

Together, these three studies make an important contribution to the higher education literature by shedding light on recent trends, documenting the tradeoffs students face as they navigate the college choice process, and developing testable ideas for how to reduce or eliminate these tradeoffs. This research is relevant to many audiences, including scholars of higher education; policymakers; high school and college administrators; and students and their families.

Study 1: Exploring the Association Between Academic Match and Bachelor's Degree Completion Over Time[1]

The U.S. has over 4,000 degree-granting colleges and universities (National Center for Educational Statistics, 2019a). Given this, it can be challenging for students to decide where to attend college. One factor that is important for students to consider, particularly if they aspire to earn a bachelor's degree or higher, is college selectivity. College selectivity refers to the competitiveness of a college's admissions process. More selective colleges admit a smaller share of applicants, and these applicants tend to have higher academic qualifications, as measured by standardized test scores, high school GPAs, and the like. More selective colleges have several advantages over less selective ones, including higher levels of per-student spending and financial aid (Bound et al., 2010; Hoxby & Avery, 2013); higher retention and graduation rates (Bowen et al., 2009; Long & Kurlaender, 2009; Shamsuddin, 2016); and better labor market outcomes, particularly for students from historically marginalized backgrounds (Black & Smith, 2006; Dale & Krueger, 2002; Hoekstra, 2009; Hoxby, 2009).

If selectivity were the only factor prospective students considered during their college search, and if colleges evaluated applicants using only academic criteria, one might expect to see a higher education system that was neatly stratified by students' academic qualifications: the students with the highest academic qualifications would attend the most selective colleges, and the students with the lowest academic qualifications would attend the least selective colleges. In this scenario, students and colleges would be perfectly matched, from an academic standpoint. In reality, many students attend colleges that are less selective than we might predict, given their

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[1] This study was published in 2022 in Volume 63 of *Research in Higher Education* (pp. 672-712).

academic qualifications. This phenomenon is called *academic undermatch*. Conversely, many students attend colleges that are more selective than we might predict. This is called *academic overmatch*.

A substantial body of research has demonstrated a link between academic match and student outcomes like graduation and post-college employment and earnings. Most studies on this topic find that students who undermatch are significantly less likely to complete a bachelor's degree than similarly qualified students, from similar backgrounds, who match or overmatch (Alon & Tienda, 2005; Bowen et al., 2009; Dillon & Smith, 2020; Ovink et al., 2018; Shamsuddin, 2016). Some studies have also found that undermatched students experience worse labor market outcomes (Dillon & Smith, 2020; Ovink et al., 2018; Zimmerman, 2014). What is more, research has shown that students from low-income, first-generation, and rural backgrounds are more likely to undermatch than their high-income, continuing-generation, and urban and suburban peers (Bastedo & Jaquette, 2011; Bowen et al., 2009; Ovink et al., 2018; Roderick et al., 2011; Smith et al., 2013). This makes undermatch a significant barrier to equity in higher education, and to social mobility more broadly.

Researchers and practitioners have worked to address this problem by developing programs and interventions to reduce the prevalence of undermatch (see Dynarski et al., 2018; Gurantz et al., 2020; Hoxby & Turner, 2013; Stephan & Rosenbaum, 2013). Thanks in part to these efforts, and to broader trends in U.S. higher education (Hoxby, 2009), rates of undermatch have declined over time (Bastedo & Jaquette, 2011; Smith et al., 2013).

There has been an extensive amount of research on academic match. However, little is known about whether the association between academic match and student outcomes has changed over time. Understanding how the association between academic match and BA completion has changed, or not, in recent years can yield important insights for policy and practice. For example, if the association is strengthening over time, then efforts to reduce the prevalence of undermatch (and, more broadly, efforts to reduce graduation rate disparities across colleges) may be more important now than they were in the past. Alternatively, if the association is weakening over time, then efforts to reduce the prevalence of undermatch may be less important than they were in the past.

Thus, while prior research has documented gaps in BA completion rates between undermatched, matched, and overmatched students, this paper seeks to describe how these gaps may be evolving. To do this, I focus on two main research questions. First, looking across multiple cohorts of college students, is academic match a consistent predictor of BA completion? Second, focusing on change over time, have undermatched, matched, and overmatched students' graduation rates increased, decreased, or stayed the same?

I examine these questions using longitudinal data from three nationally representative cohorts of first-time college students in the U.S.—students who began college in 1995, 2003, and 2011. These data come from the National Center for Education Statistics' (NCES) Beginning Postsecondary Students (BPS) surveys. To my knowledge, this is one of the only studies to analyze change over time in student outcomes by academic match,[2] and it is the first to do so using data on students who started college after 2010. It is important to note that this is a descriptive, hypothesis-generating study, not a causal, hypothesis-testing one.

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[2] Dillon and Smith (2020) examine the association between college selectivity and student outcomes for the NSLY cohorts of 1979 and 1997, whose respondents were born between 1957-64 and 1980-84, respectively.

Briefly, I find that the direction of the association between academic match and bachelor's degree completion is consistent across cohorts: holding academic and demographic characteristics constant, undermatched students are less likely to graduate, and overmatched students are more likely to graduate, than matched students. I also find that, in the aggregate, overmatched students' graduation rates have improved substantially over time, while undermatched and matched students' rates have remained stagnant. When I restrict my analysis to students who start at four-year colleges, I find that matched students' outcomes improve over time as well. Finally, when I restrict my analysis to students who start at relatively selective four-year colleges, outcomes improve across the board, regardless of match status. I offer several possible explanations for these changes over time, each of which should be explored in future research.

This study makes several contributions to the literature. Importantly, it shows that academic match continues to be a significant predictor of student success in higher education, and that it may even be growing in significance over time. This highlights the continued importance of programs and interventions that seek to reduce the prevalence of undermatch, particularly for students from low-income, first-generation, and rural backgrounds. By connecting the study's findings to broader trends in higher education, this paper also provides some working hypotheses for *why* academic match continues to be a strong predictor of student success. This sets the stage for future, hypothesis-testing research with additional implications for policy and practice.

Background

Academic Match

Researchers, policymakers, and practitioners have long been concerned with ensuring that the "right" students attend the "right" colleges. This concern is rooted in a logic of meritocracy and efficiency, or a belief that one of the purposes of higher education, and education more broadly, is to sort people by ability and prepare them for jobs and careers that match those abilities (Arum & Cook, 2018; Lemann, 2000; Sallee et al., 2008; Stevens et al., 2008). Indeed, standardized assessments like the SAT were developed to match the most academically talented students, regardless of background, with the most prestigious colleges (Lemann, 2000). In practice, these assessments have often failed to live up to this meritocratic ideal (Alon, 2009; Alon & Tienda, 2007; Fischer et al., 1996; Lemann, 2000). Nevertheless, they continue to play an important role in the college admissions process, and they reinforce the idea that a higher education system that sorts students by ability is fair, rational, and efficient.

If the meritocratic ideal is for every student to attend a college that matches his or her academic ability, the reality is much more complicated. To start with, there is little agreement among contemporary scholars about how to measure academic ability, or even the extent to which academic ability is a valid construct (Fischer et al., 1996). Given this, scholars rely on measures of *academic qualifications* or *academic preparation* (e.g., standardized test scores, high school GPA, and the like) to assess academic match. Using these measures, researchers have found that some students attend colleges that match their academic qualifications, while others do not. Definitions of match, undermatch, and overmatch can vary, but the basic idea is as follows: matched students attend colleges that, based on their precollegiate academic qualifications, we would expect them to attend. Conversely, undermatched students attend colleges that are less selective than we might expect, and overmatched students attend colleges that are more selective than we might expect. Estimates of the prevalence of undermatch vary depending on the method used and the time period covered (Rodriguez, 2015), but recent studies have found that roughly 30 to 40 percent of college students can be classified as undermatched (Bastedo & Jaquette, 2011; Ovink et al., 2018; Smith et al., 2013).

In light of this, a couple of key questions arise. First, who undermatches, and why? Second, which scenario leads to the best outcomes for individual students? Is it better to match, undermatch, or overmatch?

Who Undermatches, and Why? Much of the research on academic match over the past decade or so has focused on who undermatches and why. With regard to the question of who undermatches, scholars have consistently found that low-income, first-generation, and rural students are more likely to undermatch than their high-income, continuing generation, and urban and suburban peers (Bastedo & Jaquette, 2011; Bowen et al., 2009; Ovink et al., 2018; Smith et al., 2013). There are also some notable patterns by race and ethnicity: studies have found that White and Hispanic students are more likely to undermatch than Black and Asian students (Ovink et al., 2018; Smith et al., 2013). However, when the analysis is restricted to students with high academic qualifications, Black students are the most likely to undermatch (Ovink et al., 2018, p. 568).

Regarding the question of why students undermatch, scholars have offered a range of arguments. Using data from the Education Longitudinal Study of 2002 (ELS), Ovink et al. (2018) find that geography can play a role; students whose high schools were more than 50 miles away from a match college were 5 percentage points more likely to undermatch than students whose high schools were closer to a match college. This can help to explain why rural students have higher rates of undermatch. Another study, also using data from ELS, found that over 60 percent of students who undermatched did not submit an application to a match college (Smith et al., 2013, p. 260). Together, these findings suggest that part of the reason why students undermatch has to do with how they think about their college options. Some students may undermatch because they want or need to stay close to their hometowns. Others may undermatch due to a lack of information about college selectivity (and its association with positive student outcomes) or an incomplete understanding of the financial aid system. Still others may undermatch because selectivity is less important to them than other college characteristics (e.g., curricular offerings or student demographics), or because they are uncertain about their chances of fitting in or succeeding at a more selective college.

The Relationship Between Academic Match and Student Outcomes. To be sure, there is nothing inherently wrong with undermatching, and if it had no bearing on students' outcomes, it would not be cause for concern. However, research has consistently shown that students who undermatch are significantly less likely to graduate from college than those who match or overmatch (Alon & Tienda, 2005; Bowen et al., 2009; Dillon & Smith, 2020; Ovink et al., 2018; Shamsuddin, 2016). For example, Ovink et al. (2018) estimate that, after accounting for academic preparation, demographic characteristics, and other factors, undermatched students' probability of completing a bachelor's degree is 14 to 20 percentage points lower than that of matched or overmatched students. Some of the above-cited studies have also found that undermatched students have worse labor market outcomes than their matched and overmatched peers. It is worth noting that many of these studies employ quasi-experimental research designs (e.g., regression discontinuity or instrumental variable approaches). Thus, there is reason to believe that at least part of the relationship between academic match and student outcomes is causal, and not merely an artifact of unobserved differences between undermatched, matched, and overmatched students (e.g., higher levels of motivation amongst matched and overmatched students).

It is important to be clear about how these studies measure differences in outcomes between undermatched, matched, and overmatched students. Generally speaking, they use linear or logistic regression models to measure differences in outcomes between students who are similar in terms of academic and demographic characteristics, but who differ in terms of where they attended college. Thus, the difference in outcomes between undermatched and matched students can be thought of as a "college selectivity" coefficient. For example, if the study in question is designed to allow for causal inferences, one could say that the *impact* of undermatching is, in essence, the impact of attending a less selective college, as opposed to a more selective one.

A related body of literature looks at the relationship between college selectivity (or various measures of "college quality," which tend to be highly correlated with selectivity) and student outcomes, without explicitly classifying students as undermatched, matched or overmatched. This research finds that, on average, students tend to experience better persistence, graduation, and labor market outcomes when they attend more selective colleges, as opposed to less selective ones, net of academic qualifications and demographic characteristics (see Black & Smith, 2006; Dillon & Smith, 2020; Zhang, 2005).

In some ways, this is a more straightforward way to think about the association between college choice and student outcomes. There are, however, some advantages to categorizing students as undermatched, matched, and overmatched. One advantage is that it offers a simple way of quantifying the extent to which students from different backgrounds are making different choices about where to attend college, after accounting for differences in academic qualifications (e.g., x percent of students from lower SES backgrounds undermatch, as opposed to y percent from higher SES backgrounds). Another advantage is that the concept of academic match translates quite easily to the college application context. Indeed, it is common for high school guidance counselors to encourage students to apply to a mix of reach, match, and safety schools, with “reach” being analogous to overmatch and “safety” being analogous to undermatch (Martinez et al., 2018). If one of the goals of research is to inform policy and practice, then framing one’s research in terms that policymakers and practitioners can readily understand and apply may be worthwhile.

Efforts to Reduce Undermatch. Given that undermatched students tend to experience worse outcomes than matched and overmatched students, scholars and practitioners have developed counseling and outreach interventions that aim to reduce the prevalence of undermatch. Many of these interventions, which range from hiring college coaches to work in high schools (see Bettinger & Evans, 2019; Stephan & Rosenbaum, 2013) to guaranteeing full financial aid to prospective students from low-income backgrounds (Avery et al., 2006; Dynarski et al., 2018), have produced promising results. This suggests that, at least in some cases, counseling and outreach programs can reduce the prevalence of undermatch.

In addition to explicit efforts to reduce undermatch, several general trends in U.S. higher education have likely contributed to a decline in undermatch over time (Bastedo & Jaquette, 2011; Hoxby, 2009; Smith et al., 2013). First, the proliferation of college guides and college rankings, both in print and online, has increased students', families', and counselors' access to information about college selectivity, college resources, and student outcomes (Hoxby, 2009). Second, thanks to the Internet, the process of applying to college has become more streamlined. As a result, it is increasingly common for students to apply to several colleges of varying selectivity levels, instead of just one or two colleges (Clinedinst, 2019; Smith et al., 2013). This could increase students' chances of attending a match or overmatch college. Third, the declining cost of long-distance travel has made geographic proximity to family a less important factor in the college choice process, at least for some students (Hoxby, 2009). Combined with explicit efforts to reduce undermatch, these trends have likely contributed to an increase in academic match over time, particularly at highly selective colleges, and a corresponding decrease in undermatch. Indeed, cross-cohort research using nationally representative data suggests that undermatch, while still quite common, has declined over time (Bastedo & Jaquette, 2011; Smith et al., 2013).

Conceptual and Methodological Critiques of Academic Match. In recent years, there has been quite a bit of research on the prevalence, causes, and consequences of academic undermatch. One of the strengths of this research is that it sheds light on stratification in higher education—how colleges are stratified according to selectivity, resources, and outcomes; how students' choices about where to attend college are stratified by student-level characteristics; and how all of this contributes to the reproduction of broader social and economic inequalities.

However, it is important to acknowledge that this body of research relies on some key assumptions. (For a detailed discussion, see Bastedo & Flaster [2014] and Rodriguez [2015].) One of these assumptions is that researchers' methods for measuring academic match are valid and reliable. However, given the complex nature of the U.S. college admissions process, and the limited amount of data researchers typically have access to, there is bound to be some error in the measurement of academic match. For example, some students will be coded as undermatched when, in reality, they could not have gained admission to a more selective college. Thus, it may be best to think of academic match as a somewhat imperfect measure.

It is also important to acknowledge that the issue of stratification in U.S. higher education goes far beyond academic match. As others have pointed out, even if undermatch were completely eradicated, students from lower SES backgrounds would still be underrepresented at highly selective colleges, due to SES-related inequalities at the K-12 level (Bastedo & Jaquette, 2011). Thus, while efforts to reduce the prevalence of undermatch are valuable, they are insufficient if the ultimate goal is to significantly narrow or eliminate SES-related gaps in postsecondary outcomes. To achieve this goal, other issues must be addressed, such as the distribution of resources across colleges (Bastedo & Flaster, 2014) and the distribution of resources at the K-12 level.

In sum, despite its limitations, existing research on academic undermatch has yielded several important insights. It has shown that students who undermatch are less likely to graduate from college. It has also shown that low-income, first-generation, and rural students are the most likely to undermatch. The implication of this is that undermatching plays an important role in perpetuating social and economic inequalities in the U.S. On a more positive note, researchers have found that rates of undermatch have declined over time. What remains to be seen is whether the association between academic match and student outcomes has changed over time.

Why Might the Association Between Academic Match and BA Completion Change Over Time?

There are many factors that could cause the association between academic match and BA completion to change over time. These include the following: changes in the college-going population, changes in the distribution of resources across colleges, changes in college-level policies and practices, and changes in pre-college advising practices.

According to the Current Population Survey, the proportion of 18-to-24-year-olds in the U.S. who were enrolled in college grew from 34.3 percent in 1995 to 42 percent in 2011 (National Center for Educational Statistics, 2019b). Over the same period, the proportion of first-time college students from historically underrepresented racial and ethnic groups grew from 25 to 38 percent.[3] Meanwhile, the proportion of first-time, first-generation college students has remained relatively stable (hovering around 60 percent), as has the proportion of first-time college students who expect to earn a bachelor's degree or higher (hovering around 80 percent).[4]

As these data points illustrate, there have been some significant changes to the U.S. college-going population in recent decades. Importantly, it is larger and more racially and ethnically diverse than it once was. For this reason, studies of change over time in U.S. higher education should pay careful attention to changes in the composition of the college-going

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[3] Author's calculations using BPS data. Here, I define all students who do not identify as White or Asian as belonging to a historically underrepresented racial or ethnic group.
[4] Author's calculations using BPS data. Here, I define first-generation students as those who indicated that their most educated parent had not attained a bachelor's degree or higher. The bachelor's degree aspiration statistic for the 1995 cohort excludes those who responded "don't know" when asked about their degree aspirations.

population, to the extent possible. As I discuss in more detail in the Methods section, regression decomposition methods, such as Oaxaca-Blinder decomposition, can help to quantify the extent to which changes in outcomes are attributable to compositional changes, versus other factors (Blinder, 1973; Fairlie, 2005; Jann, 2006, 2008; Oaxaca, 1973).

It may also be important to take changes in institutional resources into account when analyzing change over time in the association between academic match and BA completion. It is well documented that more selective colleges spend more per student than less selective ones (Hoxby & Avery, 2013), and if the late-20th century trends observed by Bound et al. (2010) have continued, it is possible that resources have become even more stratified over time. If the gaps in outcomes between undermatched, matched, and overmatched students have changed, it is possible that changes in the distribution of institutional resources could help to explain this. It is beyond the scope of the present study to explicitly examine the role of institutional resources, but future research should investigate this topic.

Changes in college-level policies and practices may also be responsible for changes over time in the association between academic match and BA completion. In recent years, and particularly during the period covered by the present study (1995-2017), the U.S. higher education community has placed a growing emphasis on persistence and graduation (Kelly & Schneider, 2012; Lederman, 2010). Many refer to this as the "college completion movement." When considering the potential impact of the college completion movement on the association between academic match and BA completion, it is important to think about whether this movement is maintaining, reducing, or exacerbating graduation rate disparities across colleges. If the movement is *maintaining* disparities across colleges, then the association between academic match and BA completion may not be changing very much over time. If the movement is *reducing* disparities across colleges, then then it could be weakening the association. If, however, the movement is *exacerbating* disparities across colleges, as some scholars have worried that it might (N. Hillman, 2016), then it could be strengthening the association. It is also possible that, across all colleges, certain subgroups of students are benefitting more from the college completion movement than other subgroups of students. For example, if the movement has caused colleges to invest more resources in students who are viewed as “high risk,” from an academic standpoint, then we might expect graduation rates to increase the most for overmatched students, since they enter college with relatively low levels of academic qualifications, compared to their same-college peers. It is beyond the scope of the present study to examine the link between the college completion movement, on the one hand, and the association between academic match and BA completion, on the other, but this may be a fruitful avenue for future research.

Finally, changes in pre-college counseling and outreach programs could alter the association between academic match and BA completion. For example, if students who receive more counseling are less likely to undermatch, and if counseling has improved in quality over time (e.g., has gotten better at motivating students), this could help to explain an improvement over time in overmatched and matched students’ outcomes, and a lack of improvement over time in undermatched students’ outcomes. If the association between academic match and BA completion is changing over time, future research should investigate the potential role of pre-college counseling and outreach programs.

Data and Methods

This study uses a combination of descriptive statistics, logistic regression models, and regression decomposition methods to analyze changes over time in bachelor's degree completion rates for undermatched, matched, and overmatched students.

The data for this study come from three successive administrations of NCES's Beginning Postsecondary Students (BPS) survey: BPS 96/01, BPS 04/09, and BPS 12/17 (National Center for Educational Statistics, n.d.-a). Each of these surveys follows a nationally representative sample of first-time college students for six years after their initial enrollment in postsecondary education.[5] BPS 96/01 follows students who started college during the 1995-1996 academic year, BPS 04/09 follows students who started college during the 2003-2004 academic year, and BPS 12/17 follows students who started college during the 2011-2012 academic year. For clarity and parsimony, I refer to the three BPS cohorts as the 1995 cohort, the 2003 cohort, and the 2011 cohort.

BPS respondents include students who entered college directly after high school, as well as students who had a gap between high school and college. The BPS datasets include information on respondents' background characteristics, college experiences, college outcomes, and, if applicable, early labor market outcomes. While some variables and survey items have changed from one survey administration to another, many have stayed the same. To allow for cross-cohort comparisons, I only use variables that are consistent across the three surveys.

[5] Each cohort of first-time college students for BPS is initially recruited as part of the National Postsecondary Student Aid Study (NPSAS) (National Center for Educational Statistics, n.d.-b).

The main advantage to using BPS data over other nationally representative NCES datasets is that doing so allows me to follow a relatively recent cohort of students (students who started college in 2011) for a relatively long period of time (six years). Another NCES survey, the High School Longitudinal Study (HSLS), follows a similar cohort of students—students who, for the most part, completed high school in 2013. Compared to BPS, HSLS contains richer data on students' academic performance in high school, which would allow for more precise estimates of academic match. However, the most recent wave of HSLS data only follows students for three years after high school graduation, which is not enough time to examine bachelor's degree completion rates.

There are, however, some important limitations to the BPS data. The main limitation is that BPS has relatively little data on respondents' precollegiate academic preparation. For example, unlike other NCES surveys (e.g., HSLS, ELS, NELS), BPS does not directly assess respondents' verbal and mathematical skills in high school, nor does it collect information directly from their high schools about their GPAs or course-taking patterns. Instead, BPS relies on SAT and ACT scores, as well as the survey data that the College Board and ACT collect from the students who take these tests. If respondents have taken the SAT or ACT, then, for the most part, BPS has data on their SAT or ACT score, as well as self-reported data on their high school GPA and course-taking patterns. However, if respondents never took the SAT or ACT, then, for the most part, BPS does not contain any data on their academic performance in high school.

In short, unlike some other NCES surveys, BPS was not designed to gather comprehensive data on students' academic performance in high school. Fortunately, the majority of BPS respondents from the 1995, 2003, and 2011 cohorts took the SAT or ACT, so only a minority of students are missing data for these variables.[6] Nevertheless, it is important to acknowledge that SAT- and ACT-taking rates have risen over time, thanks in part to recently enacted state testing mandates (see Goodman, 2016; Hyman, 2017; Klasik, 2013). Because I limit my main analytic sample to SAT- and ACT-takers, this raises some concerns around sample selection bias, particularly when it comes to measuring change over time. I discuss how I address these concerns in the Methods section.

Sample

The analytic samples for the 1995, 2003, and 2011 cohorts consist of individuals who responded to all three BPS survey waves (year 1, year 3, and year 6) and had non-missing data for the outcome variables and covariates of interest.[7] For the analyses presented in this paper, the sample for the 1995 cohort includes 5,270 respondents (1,433,570, weighted). For the 2003 cohort, the analytic sample contains 9,650 respondents (1,946,370, weighted). The analytic sample for the 2011 cohort includes 12,000 respondents (2,992,650, weighted). To comply with NCES data reporting requirements, all sample sizes are rounded to the nearest ten. The sample sizes increase across the three cohorts for three main reasons: (1) growth in the overall population of first-time college students, (2) growth in the proportion of BPS respondents with non-missing SAT/ACT scores, and (3) growth in the proportion of BPS respondents with non-

[6] Most of the students who are missing ACT or SAT scores began their college careers at two-year colleges. For the 1995 and 2003 cohorts, 92 percent of students who were missing SAT or ACT scores started at two-year colleges, compared to 89 percent for the 2011 cohort. (Author's calculations using weighted BPS data.)

[7] Because the primary outcome variable for this study is bachelor's degree completion, I considered restricting the analytic sample to students who, upon entering college, reported that they expected to earn a bachelor's degree or higher. Ultimately, I decided against imposing this restriction. In part, my decision has to do with the fact that response options to the educational expectations survey item varied somewhat across survey administrations (e.g., the 1995 cohort had the option of responding "don't know," but the other cohorts did not). In addition, it is possible for students to change their educational aspirations after entering college.

missing data on other key variables. In my analysis, I use a variety of techniques to account for these changes, including testing the robustness of my results under a variety of sample specifications. To see how my sample restrictions affect the analytic sample sizes for each cohort, refer to Tables A1.1, A1.2, and A1.3. To see how the sample of SAT/ACT-takers in the BPS data compares to the sample of non-takers, refer to Table A1.4.

Variables

Bachelor's Degree Completion. Bachelor's degree completion is the outcome variable of interest for this study.[8] Individuals who complete a bachelor's degree or higher within six years of entering college are assigned a code of 1. Otherwise, they are assigned a code of 0.

Precollegiate Academic Preparation. I measure respondents' precollegiate academic preparation (academic qualifications) using three variables: SAT score, high school GPA, and highest high school math course. I use these variables because (1) prior research has shown them to be predictive of students' academic performance in college (Adelman, 1999; Alon & Tienda, 2007; Chingos, 2018) and (2) they are comparable across all three BPS surveys.

For the 2003 and 2011 cohorts, I use the derived SAT score variable that is provided by BPS (TESATDER). If respondents took the SAT, their value for this variable is their combined score on the verbal and math sections of the SAT. If they took the ACT, but not the SAT, their composite ACT score is converted to its SAT equivalent using a standard concordance table (Dorans, 1999). For the 1995 cohort, I adjust respondents' verbal and math SAT scores (TESATMRE, TESATVRE) to account for the fact that the SAT was re-centered in 1995

[8] Data for this variable come from the following BPS variables: PRENRL2B (1995), ATHTY6Y (2003), and ATHTY6Y (2011).

(Dorans, 2002). ACT composite scores (TEACTCRE) are converted to SAT scores using a standard concordance table (Dorans, 1999). To aid with interpretation, I divide SAT scores by 100 when I perform my regression analyses.

High school GPA (HCGPAREP [1995, 2003]; HSGPA [2011]) is a categorical variable with the following values: *A- to A, B to A-, B- to B, C to B-*, and *C or below*. Highest high school math course (HCMATHHI [1995, 2011], HCMATH [2003]) is a categorical variable with the following values: *Algebra 1 or Geometry, Algebra 2, Trigonometry, Pre-Calculus,* and *Calculus*. The data for both variables are self-reported; they come from the questionnaires that students fill out when they take the SAT or ACT.[9]

Selectivity of First Postsecondary Institution. Similar to many other studies of academic match (Bastedo & Jaquette, 2011; Ovink et al., 2018; Smith et al., 2013), I measure the selectivity of respondents' first postsecondary institution using a modified version of Barron's college selectivity categories. The original Barron's selectivity index organizes four-year colleges into seven categories: (1) *most competitive*, (2) *highly competitive*, (3) *very competitive*, (4) *competitive*, (5) *less competitive*, (6) *non-competitive*, and (7) *special*. To deal with small cell sizes and for the sake of parsimony, I combine categories 1 and 2 and categories 5 and 6. Also, I exclude from the analytic sample respondents who attended category 7 institutions (e.g., culinary schools and art schools), as these institutions tend to use different admissions criteria than other

[9] There is some missingness on these variables across cohorts. Approximately 500 respondents could have been added to the 1995 cohort, and 350 respondents to the 2003 cohort, were it not for missing data on the HS GPA and highest HS math course variables. No additional respondents could have been added to the 2011 cohort. For the 1995 cohort, the missingness appears to be random. For example, it is not associated with respondents' SAT scores. For the 2003 cohort, students who are missing data for the HS GPA variable score an average of 60 points lower on the SAT. Ultimately, I decided against addressing this issue via imputation, as I judged it to be relatively minor.

colleges. I also add a category for two-year and less-than-two-year colleges. My final selectivity index contains five categories: (1) *very selective*, (2) *selective*, (3) *somewhat selective*, (4) *nonselective*, and (5) *two-year or less*. Illustrative examples of colleges at each selectivity level are listed in Table A1.5.

I obtained Barron's selectivity data for 1972, 1982, 1992, 2004, 2008, and 2014 from NCES (National Center for Educational Statistics, 2017). For each year, the data contain a unique identifier for each college or university (i.e., an IPEDS ID), as well as a selectivity rating. I merge the Barron's data with the BPS data using IPEDS ID as the matching variable.[10] For the sake of simplicity and interpretability, I apply the 2014 ratings to all three cohorts. Bastedo and Jaquette (2011) use a similar approach.[11] Some respondents' colleges are not included in the 2014 Barron's selectivity ratings, even though they are listed in the BPS data as four-year institutions. Instead of automatically excluding these respondents from the analytic sample, I substitute Barron's data from 2008 or 2004, where possible. To retain as many of the remaining respondents as possible, I use Carnegie Classification data from the Integrated Postsecondary Education Data System (IPEDS) as a proxy for Barron's selectivity data.[12] This allows me to retain over 700 respondents who would have otherwise been eliminated from the analytic

[10] Many students attend multiple institutions throughout their college careers. For all the analyses in this paper, I use the IPEDS ID for the *first* college that students attended.
[11] While it is true that some colleges' selectivity ratings have changed over time, Bastedo and Jaquette (2011) find that the basic hierarchy of institutions has remained stable over time (e.g., College A and College B may have changed ratings over time, but, by and large, the position of College A relative to College B has remained stable).
[12] To do this, I used the Integrated Postsecondary Education Data System (IPEDS) to download Carnegie Classification-Undergraduate Profile data for all colleges and universities that were classified as Title IV institutions in 2012. Next, I merged this data with the 2014 Barron's selectivity ratings. Then, I determined the most common (modal) Barron's category for each Carnegie Classification. I used this to create a crosswalk between Barron's categories and Carnegie Classifications (e.g., if Carnegie = more selective, Barron's = very selective; if Carnegie = selective, Barron's = somewhat selective).

sample. Supplementary analyses show that excluding these respondents does not affect my findings; findings are robust to both sample specifications.

Academic Match. There are various methods for determining whether a student has undermatched, matched, or overmatched, each of which has its own tradeoffs and data requirements (Rodriguez, 2015). Regardless of the approach, the basic goal is to determine whether students have enrolled in colleges that are less selective than, as selective as, or more selective than we would predict, given their academic qualifications.

For this study, I determine academic match using a "perfect matching" method developed by Bastedo and Jaquette (2011). There are three basic steps to this approach.[13] The first is to rank students, separately by cohort, according to their academic qualifications. There are several ways to do this. One is to simply rank students by SAT score. Another method—the one I use for the analyses presented in this paper—is to rank students by their predicted probability of attending a very selective college, based on their full set of academic qualifications.[14] To do this, I estimate a multinomial logistic regression (mlogit) model with college selectivity as the outcome variable and SAT score, high school GPA, and highest high school math course as the predictor variables. Using the results of this model, I compute students' predicted probability of attending a very

[13] When using weighted data, I have found it necessary to perform one additional step. This involves expanding the data at the outset. By expanding the data, I mean creating *n* duplicates of each observation, where *n* is the analysis weight. This can be done using STATA's "expand" command. This ensures that, when assigning students to predicted selectivity categories, the correct number of students will be assigned to each category. Failing to do this will mean that the weighted distributions of students across predicted and actual selectivity categories will differ, when really, they should be the same. After the academic matching procedure is over, the duplicates should be deleted and the analyses should proceed in the conventional way (i.e., by using STATA's svy command to apply analytic weights).

[14] Supplementary analyses show that ranking students by SAT score produces similar results as the predicted probability method; findings are robust to both ranking methods.

selective college, and I rank them accordingly. Ties between students with the same predicted probability are broken using a random number generator, so each student has a unique rank.

Second, based on their rank, and on the actual, weighted distribution of students across colleges, students are assigned to a predicted college selectivity category. For example, if 10 percent of students in the 1995 cohort attended very selective colleges, then the top 10 percent of students from that cohort, by rank, would be coded as having a predicted college selectivity of *very selective*. These are the students who, based on their academic qualifications, we would expect to attend very selective colleges. To give another example, if 40 percent of students in a 1995 cohort attended two-year or less-than-two-year colleges, then the bottom 40 percent of students in that cohort, by rank, would be coded as having a predicted college selectivity of *two-year or less*. These are the students who, based on their academic qualifications, we would expect to attend two-year or less-than-two-year colleges.

The third step is to compare students' predicted college selectivity to their actual college selectivity (i.e., the selectivity of the college they actually attended). If students' predicted selectivity is higher than their actual selectivity, they are classified as undermatched. If it is the same, they are classified as matched. If it is lower, they are classified as overmatched. To illustrate, a student with a predicted selectivity of *selective* who actually attends a very selective college would be classified as overmatched. If the situation were reversed—if the student's predicted selectivity was *very selective* but they actually attended a selective college—they would be classified as undermatched.

Demographic Characteristics. Previous research has found that academic match and bachelor's degree completion are associated with a range of student demographic characteristics, including parental education, gender, and racial and ethnic background.[15] For this reason, I include these variables as covariates in my regression analyses. I also control for students' age and dependency status, as these are also plausible confounding variables.

BPS's parental education variable (PAREDUC) indicates the highest level of education obtained by the respondent's most educated parent. I collapse this variable into the following four categories: *high school or less, some college, bachelor's degree,* and *more than a bachelor's degree.*

Dependent status (DEPEND) is a is a dichotomous variable. I assign respondents who are claimed by their parents as financial dependents a value of 1. Financially independent students are assigned a value of 0.

Gender (SBGENDER [1995], GENDER [2003, 2001]) is a dichotomous variable. I assign women a value of 1 and men a value of 0.[16]

The BPS variables for race and ethnicity (SBRACE [1995], RACE [2003, 2011]) vary slightly across survey administrations. For this study, I create a dichotomous variable indicating whether or not the respondent identifies as a member of a racial or ethnic group that has been historically underrepresented in U.S. higher education. Respondents who identify as Black, Hispanic/Latinx, Native American, Pacific Islander, "other," or "more than one" are coded as 1. Respondents who identify as White or Asian are coded as 0.

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[15] Parental income is also a significant predictor of academic match and BA completion. However, in the BPS data, financially independent students are missing data for this variable. Because I wish to include financially independent students in my analysis, I have elected to leave parental income out of my models. In supplemental analyses, available upon request, when I restrict my analysis to dependent students, my results are unaffected by the inclusion or exclusion of the parental income variable.

[16] The BPS survey item for gender did not include an "other" or "non-binary" response option.

Because BPS includes respondents who entered college directly after high school, as well as respondents who had a gap between high school and college, I include age as a covariate in the regression models. I treat respondents' age upon college entry (AGE) as a continuous variable.

Weighting Variables. I use the appropriate BPS weighting variables for all the analyses presented in this paper. Because the analytic sample is restricted to respondents who participated in all three survey waves (year 1, year 3, and year 6), I use a panel weight that adjusts for attrition and nonresponse across survey waves (B01LWT1 [1995], WTB000 [2003, 2011]). This weight ensures that the students who responded to all three survey waves are representative of all first-time college students in the U.S. in 1995, 2003, and 2011. Of course, because the analytic sample is restricted to SAT and ACT takers, the analyses presented in this study should only be interpreted as representative of first-time college students who took the SAT or ACT.

In addition to using panel weights to adjust for attrition and nonresponse across survey waves, I use two different techniques to adjust for the complex sampling design of the BPS survey (i.e., the fact that the BPS sample was constructed by sampling colleges within strata, then students within colleges). This allows for the correct estimation of standard errors. NCES's preferred method for adjusting for complex sampling designs is to use replicate weights—either balanced repeated replicates (BRR) or Jackknife replicates (National Center for Educational Statistics, n.d.c, p. 3). I use BRR weights when conducting my cohort-by-cohort analyses (B1LBRR01-B1LBRR51 [1995], WTB001-WTB200 [2003, 2011]). An alternative to using replicate weights is a technique called Taylor series linearization. Though it is not NCES's preferred method, it is appropriate for situations where replicate weights cannot be used. This method uses information about the primary sampling unit (PSU) and strata “to produce a linear approximation for the estimate of interest, then the variance of the linear approximation is estimated using standard variance formulas” (National Center for Educational Statistics, n.d.c, p. 3). I use this method when conducting my cross-cohort analyses because the number of BRR weights varies across surveys—there are only 50 replicate weights for the 1995 cohort, versus 200 for the 2003 and 2011 cohorts.

Methods

This study focuses on two main research questions, both of which are descriptive. My first question is, looking across multiple cohorts, is academic match a consistent predictor of BA completion? My second question is, have undermatched, matched, and overmatched students’ odds of BA completion increased, decreased, or stayed the same over time?

To answer the first question, I estimate a series of binary logistic regression models, which I refer to as *cohort-specific* models.[17] Because I am interested in whether academic match is a consistent predictor of BA completion for each cohort of students, I analyze the three cohorts separately. The model for each cohort can be expressed as follows:

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 M_i + \beta_2 A_i + \beta_3 D_i + \varepsilon_i. \qquad (1)$$

This model treats students’ log odds of bachelor’s degree completion ($\log\left(\frac{p_i}{1-p_i}\right)$) as a function of academic match (M_i), precollegiate academic preparation (A_i), and demographic characteristics (D_i). Academic match is operationalized using a series of dummy variables, with

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[17] In preliminary analyses, I evaluated the appropriateness of using linear probability models with the BPS data. Across various model specifications, I found that predicted values for some observations were greater than 1 or smaller than 0. Given this, I determined that logistic regression was the most appropriate method for the present study.

matched as the omitted reference category. Precollegiate academic preparation is operationalized as students' SAT scores, high school GPA, and highest high school math course. Demographic characteristics include parental education, dependent status, race/ethnicity, gender, and age.

Because my second research question focuses explicitly on change over time, I refer to the second part of my analysis as the *cross-cohort* analysis. In this part of my analysis, I use a combination of descriptive statistics, logistic regression models, and regression decomposition methods. As I noted earlier, there are some important limitations to using the BPS data to examine change over time. Because the BPS datasets contain relatively little information on respondents' academic performance in high school, I must limit my analytic sample to students who have taken the SAT or the ACT. If SAT/ACT-taking rates had remained stable over time, I could be reasonably confident that this restriction would not interfere with my ability to make cross-cohort comparisons. However, this is not the case; the proportion of SAT/ACT-takers in the full BPS sample has grown significantly over time, from 59 percent for the 1995 cohort to 77 percent for the 2011 cohort.[18] While it is still valid to make descriptive comparisons across cohorts, we must be cognizant that differences in outcomes across cohorts could be due to many different factors. For example, as I alluded to in the Background section, they could be due to changes in higher education policy and practice. Alternatively, they could be an artifact of the sample selection process.

[18] The difference is particularly stark when looking at two-year college students; only 35 percent of two-year college students from the 1995 cohort had non-missing SAT/ACT scores, compared to 62 percent from the 2011 cohort. For four-year students, the proportion of SAT/ACT takers is relatively stable over time, rising from 91 percent for the 1995 cohort to 95 percent for the 2011 cohort. See Tables A1.2 and A1.3 for more detail.

With all of this in in mind, I begin my cross-cohort analysis by looking at how BA completion rates across college selectivity categories have changed over time, both in the full BPS sample and in the main analytic sample. To the extent that the trends are similar across both samples, I can be confident that the sample selection issue is not a major concern. This part of my analysis can also illuminate whether BA completion rates across the college selectivity spectrum have become more or less stratified over time. Next, I examine how BA completion rates for undermatched, matched, and overmatched students have changed over time. I examine aggregate completion rates, as well as completion rates for students within each college selectivity category. This provides some initial insight into the question of whether undermatched, matched, and overmatched students who attend the same types of colleges have experienced similar trends over time. These simple descriptive analyses highlight important patterns in the data, but they are limited insofar as they fail to account for potential confounding variables. For example, if overmatched students are seeing increases in their graduation rates, part of this increase could be attributable to changes in overmatched students' academic qualifications, or to changes in the types of colleges they are attending.

Thus, in the second part of my cross-cohort analysis, I estimate a series of binary logistic regression models. These models pool together the data from the 1995, 2003, and 2011 cohorts, and they look at undermatched, matched, and overmatched students separately.[19] The purpose of these models is to test whether the cross-cohort differences in graduation rates for undermatched, matched, and overmatched students are statistically significant, after controlling for cross-cohort

[19] It is also possible to estimate a single model for all students, with a cohort-by-match status interaction. This model answers a slightly different question, which is, have the gaps in graduation rates between undermatched, matched, and overmatched students changed over time? See Table A1.6 for results from such a model.

differences academic preparation, demographic characteristics, and college selectivity. In other words, they help to answer the following question: after controlling for observable characteristics, have bachelor's degree completion rates for undermatched, matched, and overmatched students improved over time, declined, or remained the same? The model for each group can be expressed as follows:

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 A_i + \beta_2 D_i + \beta_3 S_i + \beta_4 C_i + \varepsilon_i. \quad (2)$$

This model treats students' log odds of bachelor's degree completion ($\log\left(\frac{p_i}{1-p_i}\right)$) as a function of precollegiate academic preparation (A_i), demographic characteristics (D_i), college selectivity (S_i), and cohort (C_i). Academic preparation and demographic characteristics are operationalized in the same way as the first set of models. College selectivity is operationalized using a series of dichotomous variables, with *somewhat selective* serving as the omitted reference category.[20] Cohort is operationalized as a series of dichotomous variables, with the 1995 cohort serving as the omitted reference category. While these models do a good job of controlling for changes in *observed* student-level characteristics over time, they cannot account for changes in *unobserved* student-level characteristics. Thus, when interpreting these results, it is important to consider the possibility that they are being driven, at least partially, by unobservable changes in student-level characteristics. It is also possible, of course, that the changes are being driven by other factors, such as policies and practices that were motivated by the college completion movement, changes in the distribution of resources across colleges, or changes in pre-college advising practices.

[20] In the cross-cohort models, I control for college selectivity because I am analyzing undermatched, matched, and overmatched students separately.

The final step of my cross-cohort analysis is to use Oaxaca-Blinder decomposition, a regression decomposition method, to quantify the extent to which cross-cohort differences in BA completion rates can be attributed to cross-cohort differences in observable characteristics. This helps to provide some additional context for interpreting the logistic regression results. Briefly, regression decomposition separates differences in outcomes between two groups into two parts: a part that is attributable to between-group differences in observed characteristics (i.e., differences in endowments), and a part that is due to other factors (i.e., differences in coefficients or differences in unobserved characteristics) (Blinder, 1973; Fairlie, 2005; Jann, 2008; Oaxaca, 1973). For example, if I find that overmatched students from the 2011 cohort have a higher graduation rate than their 1995 counterparts, regression decomposition can quantify the extent to which this can be explained by between-cohort differences in overmatched students' observed characteristics. Regression decomposition methods have typically been used to analyze differences in outcomes by race, ethnicity, and gender (see Bielby et al., 2014; Blinder, 1973; Fairlie & Robb, 2007; Oaxaca, 1973), but they have also been used to examine change over time (see Fortin et al., 2010; Percheski, 2017). It is important to note that regression decomposition is not designed to address concerns related to selection bias; to the extent that the cross-cohort regression models are affected by selection bias, these results will also be affected.

In the context of an OLS regression, a regression decomposition can be expressed as follows:

$$\bar{Y}_A - \bar{Y}_B = (\bar{X}_A - \bar{X}_B)\hat{\beta}_A + \bar{X}_B(\hat{\beta}_A - \hat{\beta}_B) \tag{3}$$

where $\bar{Y}_A - \bar{Y}_B$ is the difference between the groups' means on the outcome variable, $(\bar{X}_A - \bar{X}_B)\hat{\beta}_A$ is the explained part of the difference, and $\bar{X}_B(\hat{\beta}_A - \hat{\beta}_B)$ is the unexplained part of the difference (Jann, 2008; Sinning et al., 2008).

In the context of logistic regression, which is nonlinear, the basic logic of a regression decomposition is the same. However, because the conditional expectation of the outcome variable, E(Y|X), is not necessarily equal to the mean of the covariates multiplied by the regression coefficients, $\bar{X}\hat{\beta}$, the underlying math is slightly different (Sinning et al., 2008). Thus, a nonlinear regression decomposition is best expressed in terms of conditional expectations, as follows:

$$\Delta_A^{NL} = \{E_{\beta_A}(Y_{iA} \mid X_{iA}) - E_{\beta_A}(Y_{iB} \mid X_{iB})\} + \{E_{\beta_A}(Y_{iB} \mid X_{iB}) - E_{\beta_B}(Y_{iB} \mid X_{iB})\} \qquad (4)$$

where Δ_A^{NL} is the difference in outcomes between group A and group B, the first bracketed expression is the explained part of the difference, and the second bracketed expression is unexplained part of the difference.

There are various statistical packages that can perform nonlinear regression decompositions (Jann, 2006, 2008; Sinning et al., 2008). For the analyses presented in this paper, I use STATA's "oaxaca" command with the "logit" option (Jann, n.d.). Supplemental analyses show that different packages (e.g., STATA's "fairlie" command) yield similar results.

Results

Table 1.1 describes the analytic sample for each cohort.[21] As the table shows, the prevalence of undermatch, match, and overmatch across cohorts is relatively stable over time.

[21] For descriptive statistics that are broken down by academic match, refer to Table A1.7.

Across all three cohorts, roughly 30 percent of students can be classified as undermatched, 40 percent as matched, and 30 percent as overmatched. This stands in contrast with other cross-cohort studies of academic match, which show that undermatch has declined over time (Bastedo & Jaquette, 2011; Smith et al., 2013). I argue that this is an artifact of how I constructed my analytic sample. Whereas other studies include high school graduates who never attend college, coding all of them as undermatched, the present study, because it relies on BPS data, is restricted to college goers. If my data allowed me to include individuals who did not attend college, I would likely have found a decline in undermatch as well, due to increases in college-going rates over time. Alternative matching techniques, such as those that rely on respondents' college application data (something that is not available in from the BPS surveys), may have also shown a decrease in the rate of undermatch over time.

Turning to the measures of precollegiate academic preparation, there are some fluctuations over time, but no clear trends. Regarding demographic characteristics, the most notable change is an increase in the proportion of students from historically underrepresented racial and ethnic backgrounds. These students make up 20 percent of the analytic sample for the 1995 cohort, compared to 36 percent for 2011 cohort. There is a similarly large increase over time in the proportion of students from historically underrepresented racial and ethnic backgrounds in the full BPS sample. Looking at college selectivity, there has been a 7 percentage-point increase in the share of students who start at two-year or less-than-two-year colleges, and a corresponding decrease in the share of students who start at very selective, selective, and somewhat selective colleges. This, to some extent, is due to sample selection issues stemming from rising SAT/ACT-taking rates, as opposed to population-level changes in the distribution of students across colleges. Indeed, in the full BPS sample, the proportion of students who start at two-year and less-than-two-year colleges declines over time, from 59 percent for the 1995 cohort to 45 percent for the 2011 cohort. Finally, looking at the outcome variable of interest, we can see that overall BA completion rates remain stable over time, hovering just below 50 percent. Again, this trend may be affected by sample selection issues; when we look at the full BPS dataset, BA completion rates increase over time, from 29 percent for the 1995 cohort to 38 percent for the 2011 cohort.[22,23]

Cohort-specific Results

Selected results from the cohort-specific logistic regression models are reported in Table 1.2. Recall that these models compare undermatched, matched, and overmatched students to see whether academic match is a significant predictor of BA completion across all three cohorts, after controlling for differences in academic preparation and demographic characteristics. When I estimate these models using the full analytic sample (see Panel 1 of Table 1.2), I find that undermatched students have lower odds of graduating than matched students, while overmatched students have higher odds. For example, for the 2011 cohort, undermatched students' odds of BA completion are 41.4 percent as large as matched students' odds. For the same cohort, overmatched students' odds of BA completion are 3.4 times larger than those of matched students. If we translate these into predicted probabilities, holding all covariates at their means, the predicted probability of BA completion for undermatched, matched, and overmatched

[22] All statistics pertaining to the full BPS sample are from the author's calculations using weighted BPS data.
[23] Part of the increase over time in BA completion rates may also be attributable to improvements in BPS survey administrators' ability to track students using administrative data systems like the National Student Clearinghouse (X. Chen, 2019, p. B-14).

students from the 2011 cohort is 32 percent, 46 percent, and 64 percent, respectively. These patterns are consistent across cohorts, and they align with prior research on academic match and BA completion. For full results from these models, refer to Table A1.8.

An important point to remember, when interpreting these results, is that these models do not control for college selectivity. Thus, a logical way to interpret the undermatch and overmatch coefficients is to view them as "college selectivity" coefficients. In other words, these results show that undermatched students have a lower likelihood of graduating than similarly qualified students from similar backgrounds who attend more selective colleges, and overmatched students have a higher likelihood of graduating than similarly qualified students from similar backgrounds who attend less selective colleges.

One question that arises when looking at the results presented in Panel 1 is, would the same patterns hold if we restricted the analysis to four-year college goers? Would overmatched students still have higher odds of graduating than matched students, and would undermatched students still have lower odds? To answer this question, I restricted the analytic sample to students who were academically qualified to attend four-year colleges, according to my matching method, and who actually started their college careers at four-year colleges. When the cohort-specific regression models are estimated using this restricted sample, I find that overmatched students' advantage decreases but remains statistically significant (see Panel 2 of Table 1.2). Undermatched students' disadvantage also decreases but remains statistically significant for two of the three cohorts. What these descriptive results suggest is that part of overmatched students' advantage may come from their avoidance of two-year colleges, but that this alone cannot explain the overall gap in graduation rates between overmatched and matched students.

Similarly, part of undermatched students' disadvantage may come from the fact that they often begin their college careers at two-year and less-than-two-year colleges, but this alone cannot explain the overall gap in graduation rates between matched and undermatched students.

Continuing along this line of inquiry, the third panel of Table 1.2 presents results from models that focus on students who were academically qualified to attend one of the top three categories of colleges (somewhat selective, selective, or very selective), and who actually attended one of these colleges. Using this sample specification, I find that overmatched students' advantage over matched students persists, but that undermatched students' disadvantage diminishes. Indeed, for the 1995 and 2003 cohorts, there is no longer a statistically significant difference between undermatched and matched students when it comes to BA completion. What these results suggest is that, at least for the 1995 and 2003 cohorts, students who undermatch at selective or somewhat selective colleges do not face a substantial penalty for doing so. To be sure, these students represent a modest subset of the total sample of undermatched students (roughly 35 percent for both cohorts), so it remains true that, in most cases, undermatching is associated with a lower likelihood of graduation. Furthermore, it is important to note that, for the 2011 cohort, there is still a statistically significant difference between undermatched and matched students' graduation rates.

Cross-cohort Results

Descriptive Analysis. Figure 1.1 shows BA completion rates by cohort and college selectivity for the full BPS sample (top panel) and the main analytic sample (bottom panel).[24] Recall that the full BPS sample includes SAT/ACT-takers as well as non-takers. Looking at both

[24] Refer to Table A1.9 to view this data in table form.

panels, we see that BA completion rates increase over time at the top three categories of colleges (somewhat selective, selective, and very selective), and decrease slightly at nonselective four-year colleges. We see diverging patterns when it comes to students who start at two-year and less-than-two-year colleges (hereafter, I refer to these as two-year colleges). In the full BPS sample, BA completion rates are increasing slightly for this group of students, but in the analytic sample, they are decreasing.

One of the clear patterns to emerge from Figure 1 is that, over time, the top three categories of colleges are pulling ahead while the bottom two categories are relatively stagnant. For example, looking at the analytic sample for 1995, the BA completion gap between students who started nonselective and somewhat selective colleges was 5 percentage points. By 2011, this gap had grown to 10 percentage points. This suggests that, in some respects, graduation rates have become increasingly stratified by college selectivity.

Returning to the difference in trends for two-year starters in the full BPS sample and the main analytic sample, this difference is likely attributable to the fact that, over time, the proportion of two-year college students who are eligible for inclusion in the analytic sample increases substantially, largely thanks to increases in SAT- and ACT-taking rates. Indeed, the proportion of two-year starters who make it into the analytic sample grows from 26 percent for the 1995 cohort to 62 percent for the 2011 cohort, an increase of 36 percentage points. The proportion of four-year college students who make it into the analytic sample also increases substantially, from 70 percent to 95 percent, though this has less to do with changes in SAT and

ACT-taking rates and more to do with unrelated missing data issues.[25] In any event, for two-year and four-year students alike, the analytic sample for 1995 may differ in significant ways from the analytic sample for 2011. To the extent that the differences between the two cohorts are observable (e.g., differences in demographic characteristics), I can account for them in regression models by including them as control variables. To the extent that they are unobservable (e.g., differences in motivation), they may bias my results, most likely in a negative direction (i.e., masking potential improvements over time). Still, it is important to bear in mind that, even in the full BPS sample, BA completion rates for students who start at two-year colleges only improve by 3 percentage points across cohorts, while BA completion rates for students who start at somewhat selective, selective, and very selective colleges improve by 14, 14, and 9 percentage points, respectively. Thus, the basic argument holds that BA completion rates for students at relatively selective colleges have improved quite a bit, while BA completion rates for students at open-access institutions have not.

Table 1.3 presents cohort-by-cohort graduation rates by academic match and college selectivity. Overall, the bachelor's degree completion rate for undermatched students decreases from 52 percent (1995 cohort) to 46 percent (2011 cohort). Matched students' completion rate also decreases from 43 to 38 percent.[26] By contrast, overmatched students' completion rate increases substantially from 54 to 64 percent. If we break these graduation rates down by college selectivity, some notable patterns emerge. First, regardless of match status, graduation rates are

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[25] Refer to Tables A1.2 and A1.3 to see how the various sample restrictions affect two-year and four-year college goers.

[26] If it seems strange that matched students' graduation rates would be lower, in the aggregate, than undermatched students', it can be helpful to remember than roughly 50 percent of matched students "match" into two-year or less-than-two-year colleges (see Table A1.7).

increasing over time at the top three categories of colleges (very selective, selective, and somewhat selective). Second, within selective and somewhat selective colleges, graduation rates are increasing the fastest for overmatched students, followed by matched and undermatched students, respectively. Third, there are inconsistent trends by match status at nonselective colleges; undermatched students' graduation rates decline over time, matched students' increase, and overmatched students' remain relatively stagnant. Relatively few students attend nonselective colleges, and even fewer match into nonselective colleges (see Table A1.7), so these trends should be interpreted with caution. Finally, graduation rates at two-year colleges decline over time. However, this pattern should also be interpreted with caution, due to sample selection concerns.

Logistic Regression Results. Selected results from the cross-cohort regression models are reported in Table 1.4. Full results are reported in Table A1.10. For these models, data from the 1995, 2003, and 2011 cohorts are pooled, and undermatched, matched, and overmatched students are analyzed separately. When I estimate these models using the main analytic sample (see Panel 1 of Table 1.4), I find that outcomes for undermatched and matched students do not improve over time (the cohort coefficients are not significant), but that the opposite is true for overmatched students (the 2011 cohort coefficient is significant).[27] Indeed, after controlling for academic preparation, demographic characteristics, and college selectivity, overmatched students

[27] In supplementary analyses, I examine whether including non-test-takers in my sample and coding them as undermatched or matched would change my results. When non-takers are coded as undermatched and pooled with the data for undermatched students, the results are similar to the results from the main model specification. However, when non-takers are coded as matched and pooled with the data for matched students, I find a statistically significant improvement over time. Though there are some limitations to this model (e.g., it is unable to adequately control for non-takers' academic qualifications), it does suggest that my main specification could be underestimating the extent to which matched students' outcomes improve over time. See Table A1.11 for more details.

from the 2011 cohort's odds of graduating are roughly 1.5 times greater than those of their 1995 cohort counterparts. This confirms that outcomes for overmatched students have improved over time, net of observables.

To examine these results in more depth, I restrict the analytic sample to students who were predicted to attend a four-year college and who actually attended a four-year college (see Panel 2 of Table 1.4). When the cross-cohort regression models are estimated using this restricted sample, I find that undermatched students' graduation rates still do not differ significantly across cohorts, but that matched and overmatched students' do. Indeed, when the analysis is restricted in this way, we see that matched students from the 2011 cohort's odds of graduating are 1.7 times higher than those of their 1995 counterparts. Similarly, overmatched students from the 2011 cohort's odds of graduating are still 1.5 times higher than those of their 1995 counterparts.

Continuing along this line of inquiry, I further restrict the analytic sample to students who were predicted to attend one of the top three categories of colleges, and who actually attended one of these colleges (see Panel 3 of Table 1.4). When the cross-cohort models are estimated using this sample specification, I find a few notable differences, compared to the previous two specifications. First, I find that, for this subset of students, graduation rates improve over time regardless of match status. This aligns with the descriptive statistics presented in Table 1.3. Another interesting finding is that, for undermatched and matched students, the 2003 cohort coefficient is statistically significant, as well as the 2011 cohort coefficient. This suggests that, at least for these two subgroups, graduation rates started improving relatively early on.

Regression Decomposition Results. Table 1.5 presents results from the nonlinear Oaxaca-Blinder regression decompositions. The decompositions in Table 1.5 use the same model specification as the cross-cohort regression models described above. However, because regression decompositions are only designed to compare two groups, the 2003 cohort is excluded. Panel 1 of Table 1.5 shows results from the main analytic sample. Focusing on undermatched students first, Panel 1 shows that the raw difference in graduation rates between the 1995 and 2011 cohorts is 5.9 percentage points. When this difference is decomposed, roughly five-sixths of it can be explained by changes in observed characteristics (i.e., endowments), and one-sixth can be attributed to other factors. This helps to explain why the 2011 cohort coefficient in the cross-cohort regression model was not statistically significant, even though the raw difference in outcomes between cohorts was quite large; after controlling for cross-cohort differences in observable characteristics, undermatched students from the 1995 and 2011 cohort had similar odds of completing a BA.

Looking at matched students next, the raw difference in graduation rates between the 1995 and 2011 cohorts is 4.7 percentage points. As was the case with undermatched students, the first part of the decomposition shows that matched students in 2011 have somewhat weaker endowments than their 1995 counterparts. Putting this into counterfactual terms, we can interpret the first part of the regression decomposition as follows: if matched students in 2011 had the same characteristics (endowments) as their 1995 counterparts, we would expect their graduation rate to be 7.4 percentage points higher. The second part of the decomposition, which is negative, reveals that some of this disadvantage is counteracted by other factors—factors that cannot be explained by the regression model.

Turning to overmatched students, Panel 1 shows that the raw difference in graduation rates between the 1995 and 2011 cohorts is 10 percentage points. The first part of the decomposition reveals that only a small share of this difference, 0.5 percentage points, can be attributed to differences in observed characteristics across cohorts. Putting this into counterfactual terms, if overmatched students in 2011 had the same characteristics as their 1995 counterparts, their graduation rate would decrease by 0.5 percentage points, bringing the between-cohort gap in graduation rates down to 9.5 percentage points. This means that a large share of the difference in graduation rates—95 percent—is attributable to other factors.

To examine these results in more depth, I restricted the analytic sample to students who were predicted to attend a four-year college, and who actually attended a four-year college (see Panel 2 of Table 5). When I perform the regression decomposition using this restricted sample specification, I find that graduation rates for the 2011 cohort are higher than graduation rates for the 1995 cohort, and that the cross-cohort difference in graduation rates for undermatched, matched, and overmatched students is 1.6, 8.0, and 8.0 percentage points, respectively. For all three groups, almost none of this difference can be explained by cross-cohort differences in observed characteristics. This means that a large share of the difference in graduation rates for this restricted sample is attributable to other factors. Panel 3 shows that the results are quite similar when the sample is restricted to students who were predicted to attend one of the top three categories of colleges, and who actually attended one of these colleges. One nuance to note is that, for undermatched students, the difference between the 1995 and 2011 cohort, net of covariates, is no longer statistically significant when the 2003 cohort is excluded from the model.

Discussion and Conclusion

Prior research has documented a significant association between academic match and student outcomes in the U.S. The present study uses data from three nationally representative cohorts of first-time college students to explore whether this association has evolved over time. I find that some aspects of the association have remained stable, while other aspects have changed.

First, I find that the direction of the association between academic match and bachelor's degree completion is consistent across cohorts: holding academic and demographic characteristics constant, undermatched students are consistently less likely to graduate, and overmatched students are consistently more likely to graduate, than matched students. This reinforces a common finding from prior research: on average and regardless of academic preparation and demographic characteristics, students' likelihood of graduating improves when they attend more selective colleges (Bowen et al., 2009; Dillon & Smith, 2020).

Second, I find that, in the aggregate, overmatched students' graduation rates have improved substantially over time, while undermatched and matched students' rates have not. When the sample is restricted to those who start at four-year colleges, I find that graduation rates for matched students have improved as well. When the sample is further restricted to students who start at one of the top three categories of colleges, I find that graduation rates have improved across the board. Part of the reason for these findings is that graduation rates at somewhat selective, selective, and very selective colleges—which have larger shares of overmatched students—have increased substantially over time, while graduation rates at nonselective and two-year colleges—which have larger shares of undermatched students—have been relatively stagnant. Another important pattern to note is that, at somewhat selective and selective colleges, overmatched students have seen the largest gains over time, followed by matched and undermatched students.

Third, I find that only a small portion of the improvement in overmatched students' graduation rates can be explained by cross-cohort differences in their academic qualifications, demographic characteristics, and college destinations. In other words, overmatched students from the 2011 cohort are not graduating at higher rates than their 1995 counterparts simply because they have higher academic qualifications or different demographic characteristics, or because they are attending more selective colleges. Similarly, when the analysis is restricted to four-year college goers, and to students who attended one of the top three categories of colleges, most of the changes over time—for undermatched, matched, and overmatched students alike—cannot be explained by cross-cohort differences in observable characteristics.

This study makes a valuable contribution to the literature on academic match. From a practical standpoint, it highlights the continued importance of programs and interventions to reduce the prevalence of undermatch, particularly for students from low-income, first-generation, and rural backgrounds. It also highlights the continued importance of efforts to reduce disparities in graduation rates across colleges. However, it is not without limitations. Most significantly, more research is needed to understand *why* outcomes for some students have improved, while outcomes for other students have not. One possibility, which I articulate in the Background section, is that recent pressures to improve graduation rates (i.e., the college completion movement) have exacerbated graduation rate disparities across colleges. However, this is not the only possibility. Other factors, such as changes in the distribution of resources across colleges (unrelated to the college completion movement) and changes in pre-college advising, could also be responsible for these trends. It may also be the case that students from the 2011 cohort differ in some unobserved, but significant, way from their 1995 counterparts, either due to population-level changes over time, or due to sample selection issues. Future research, using other datasets and causal research designs, should explore these hypotheses.

Several other limitations are also worth noting. First, while prior research has documented a causal relationship between academic match and student outcomes, the present study, due to data limitations, was not designed to allow for causal inferences. Therefore, the analyses presented herein should be interpreted as descriptive and exploratory. Second, as I have noted throughout, while there are several important advantages to using BPS data for this study, there are also some disadvantages. The main disadvantage, compared to other NCES datasets, is the lack of comprehensive data on students' academic performance in high school. This significantly limits the analytic sample. Thus, while it is true that the BPS data are nationally representative of all first-time college students, the analyses presented in this study should only be generalized to first-time college students who took the SAT or ACT. In addition, because SAT/ACT-taking rates have changed over time, there may be some unobserved differences between students from the 1995 cohort and the 2011 cohorts, particularly amongst two-year college students. This may bias my results to some extent. Third, as other scholars have articulated in greater depth, the concept of academic match is, in itself, limited (Bastedo & Flaster, 2014; Rodriguez, 2015). Importantly, whether a student is classified as undermatched,

matched, or overmatch will depend, in part, on the data that are available and the methods that are employed.

In spite of these limitations, this study adds to our understanding of academic match and generates new hypotheses that can be tested in future research. Ultimately, by describing the association between academic match and student outcomes for a very recent cohort of students, and by situating these findings in a historical context, this study sets the stage for future research on *how* and *why* academic match continues to be a significant predictor of student outcomes.

Study 2: College Proximity and College Costs: Is it More Expensive to Attend a Far-away College?

Geography plays an important role in the college choice process. While it is true that some students are eager to attend colleges that are far from their hometowns, the more common scenario is for students to attend colleges that are close to home (Alm & Winters, 2009; Griffith & Rothstein, 2009; Long, 2004; Mountjoy, 2022; Rouse, 1995). However, attending a nearby college may not always be possible, and even if it is, it may not be the optimal choice. This is especially true for those who live in areas with limited college options, or in areas where the local colleges are under-resourced, relative to those that are farther away. Indeed, when people live near colleges with more resources and higher graduation rates, such as four-year and selective four-year colleges, they tend to experience better graduation and labor market outcomes than those who live farther away (Card, 1995; Long & Kurlaender, 2009; Shamsuddin, 2016).

Why do people tend to enroll in colleges that are close to home, even when farther ones may offer better outcomes? One plausible explanation has to do with information. That is, people may attend nearby colleges because it is easier to access information about them (Do, 2004; Griffith & Rothstein, 2009). Social ties—a need or desire to stay close to family and friends—may also contribute to this phenomenon (Desmond & Turley, 2009; Goldrick-Rab, 2017; Núñez & Bowers, 2011; Ovink & Kalogrides, 2015; Turley, 2009). Cost may be a factor as well. If it is more expensive to attend a far-away college, this could help to explain why people tend to stay close to home (Briscoe & De Oliver, 2006; Card, 1995; Dillon & Smith, 2017; Do, 2004; Griffith & Rothstein, 2009; Rhodes, 2021; Spiess & Wrohlich, 2010; Turley, 2009).

To be sure, the college choice process is complex, and all three factors—information, social ties, and cost—could play an important role. Still, despite the long-recognized importance of college affordability in higher education policy discussions, there has been little empirical research on the relationship between college proximity and college costs. Relatedly, there has been little empirical research on the relationship between *geographic access* and college costs. By geographic access, I mean the extent to which people live in areas with abundant or limited college options. Someone who lives in an area where colleges are few and far between can be said to have a low level of geographic access. Conversely, someone who lives in an area with many colleges can be said to have a high level of geographic access.

The present study addresses this gap in the literature by examining the following three research questions. First, do students with lower levels of geographic access travel longer distances to attend college? Second, do students who travel longer distances face higher college costs? Third, do students with lower levels of geographic access face higher costs and, if so, could this be because they travel longer distances? I hypothesize that students with lower levels of geographic access will travel longer distances, and that students who travel longer distances will face higher costs. Further, I hypothesize that there will be an association between these two things, such that students with lower levels of geographic access will face higher costs.

To answer these questions, I use data from the High School Longitudinal Study of 2009 (HSLS:09), a nationally representative survey that follows a sample of ninth grade students from 2009 until several years after high school. I measure geographic access and distance traveled using information about the location of students' hometowns, the location of nearby colleges, and the location of students' initial college destinations. HSLS does not contain a comprehensive measure of the costs of college, so I focus on student debt, an important indicator of college costs.[28] In measuring student debt, I focus on the amount of debt that students accumulate during the first year of college. All three research questions are descriptive in nature. I investigate them using a combination of descriptive statistics and regression analysis. In my regression models, I control for a range of potential confounding factors, including socioeconomic status, race/ethnicity, and high school GPA.

Consistent with my first hypothesis, I find that students with lower levels of geographic access tend to travel longer distances to attend college. Consistent with my second hypothesis, I find that students who travel longer distances tend to accumulate more student debt. I find modest support for my third hypothesis. Specifically, I find suggestive evidence that students with lower levels of geographic access accumulate larger amounts of debt. However, these results are not precisely estimated, so they should be interpreted with caution.

This study makes a valuable contribution to the literature on geographic inequality in higher education by investigating whether geographic access could be related to college costs and, more specifically, student debt. It also contributes to the literature on college choice by assessing the plausibility of the "cost hypothesis," as it relates to college proximity and college choice. These descriptive insights pave the way for future research on geographic access, college

[28] Prior research has shown that there is a positive association between student debt and college costs (Furquim et al., 2017; Houle, 2014). However, it is important to acknowledge that student debt is not a comprehensive measure of college costs. This is because, in addition to taking on debt, students may use personal or family savings to pay for college. They may also work a part-time or full-time job. That said, student debt is a policy-relevant measure, as debt loads have grown substantially in recent decades, and as evidence has grown that student debt can have a significant, negative impact on people's lives after college (Gicheva, 2016; Kuperberg & Mazelis, 2022; Mezza et al., 2019; Minicozzi, 2005; Rothstein & Rouse, 2011; Tabit & Winters, 2019). I discuss this issue in more detail in the Data and Methods section of this paper.

choice, and college costs, including research that uses experimental or quasi-experimental methods. Additional research in this area could be one of the keys to understanding, and ultimately remedying, geographic inequalities in postsecondary outcomes.

The remainder of this paper proceeds as follows. I begin by situating this project within the existing literature on college proximity and college choice. Next, I describe the data and methods I use to answer my research questions. Following that, I present the results from my descriptive analyses and regression models. I conclude with a discussion of this study's implications for policy, practice, and future research.

Background

College Choice: Theoretical Perspectives and Empirical Findings

For decades, scholars have sought to understand the factors that shape people's decisions about whether, and where, to attend college. Many have examined this topic through the lens of human capital theory, which argues that people make decisions about educational investments by weighing the expected costs and benefits of those investments (Becker, 1964). Thus, a person will attend college if the expected benefits outweigh the expected costs. Similarly, a person's choice about which college to attend will be shaped by a cost-benefit calculation.[29]

Others have examined college choice through the lens of social capital theory. Social capital theory sees people's knowledge and dispositions about college as being shaped by their social networks (Sewell et al., 1969). This can help to explain why people from different social

[29] Costs and benefits, according to human capital theory, need not be financial. They may also be psychological or social, for example.

backgrounds might make different choices about whether and where to attend college, despite having similar academic qualifications.

Another group of scholars have emphasized the multi-step nature of the college choice process. For example, Toutkoushian & Paulsen (2016) break the college choice process into five steps: predisposition, initial search, application, admission, and enrollment. Multi-step models highlight the importance of viewing college choice as multi-year process, rather than something that happens during the senior year of high school.

Each of these theories offers a unique perspective on the college choice process. That said, they provide little insight into the costs or benefits of attending different types of colleges. The empirical research on college choice can be informative on this point. This research has provided compelling evidence that those who attend four-year instead of two-year colleges, or more selective instead of less selective colleges, tend to experience better graduation and labor market outcomes, all else being equal (Bowen et al., 2009; Dillon & Smith, 2020; Ovink et al., 2018; Roderick et al., 2011; Shamsuddin, 2016). This empirical pattern may help to explain why, in many cases, students will try to attend the most selective college possible, given their academic qualifications (Bound et al., 2009; Hoxby, 2009; Sallee et al., 2008).

In some cases, however, students do *not* attend the most selective college possible. This phenomenon is known as academic undermatch, or simply “undermatch.” A common example of undermatch is when a student with the academic qualifications to attend a four-year college ends up enrolling at a two-year college instead. Students who undermatch tend to experience worse graduation and labor market outcomes than those who “match” (attend colleges that are more closely aligned with their academic qualifications) or “overmatch” (attend colleges that appear to exceed their academic qualifications; Bowen et al., 2009; Cook, 2021; Dillon & Smith, 2020; S. Ovink et al., 2018). This may be because, in general, undermatching means attending a college with fewer resources (see Hoxby, 2009). Peer effects may also help to explain why those who match or overmatch tend to experience better outcomes than those who undermatch (Winston, 1999).

There are numerous factors that are associated with a person's likelihood of undermatching, including socioeconomic status and race/ethnicity (Dillon & Smith, 2017; Smith et al., 2013). In addition, one of the most consistent predictors of undermatch is *college proximity*; people who live far away from the nearest match college are more likely to undermatch than people who live in close proximity to a match college (Dillon & Smith, 2017; Ovink et al., 2018). This finding is part of a larger body of research on college proximity and college choice, which has found that, in general, the closer a student is to a particular college, the more likely they are to attend that college (Alm & Winters, 2009; Griffith & Rothstein, 2009; Long, 2004; Mountjoy, 2022; Rouse, 1995).

College Proximity and College Choice

Much of the research on college proximity and college choice has been motivated by a desire to understand the causal impacts of different types of college choices. For example, Long and Kurlaender (2009) use college proximity as an instrumental variable to investigate whether starting at a two-year college, versus a four-year college, hinders a person's chances of earning a four-year degree. Similarly, Card (1995) uses college proximity to identify the causal impact of years of education on earnings. For these scholars, college proximity is meaningful because it is a quasi-random factor that affects people's choices about whether and where to attend college.

Their goal is not to explain *why* college proximity affects people's choices, but rather to use the fact that it affects their choices to answer other important questions.

That said, some of the research on college proximity and college choice does engage, in a more substantive way, with the concept of college proximity. For example, Ovink et al. (2018) show that living within 50 miles of a match college has an impact on students' chances of matching and, consequently, an impact on their chances of earning a bachelor's degree. The authors use this finding to call attention to the fact that a particular subset of students—those who live far away from match colleges—are at a distinct disadvantage when it comes to earning a bachelor's degree. This highlights an important, but often under-acknowledged, dimension of inequality in higher education: geographic inequality.

Other research on geographic inequality in higher education has explored the association between college proximity and sociodemographic factors like class and race. One of the findings from this line of research is that there tend to be more colleges—both two-year and four-year—in communities with higher levels of educational attainment and larger shares of White and Asian residents (N. W. Hillman, 2016). Conversely, there tend to be fewer colleges in communities with lower levels of educational attainment and larger shares of Hispanic residents. This is not simply a rural versus urban issue; some rural areas have abundant supplies of colleges, while some urban areas do not (ibid). In this paper, I describe people who live in areas with limited supplies of colleges as having a low level of geographic access to higher education. Conversely, I describe people who live in areas with abundant supplies of colleges has having a high level of geographic access.

Given the link between college proximity, college choice, and college outcomes, it stands to reason that socioeconomic and racial/ethnic disparities in geographic access can help to explain socioeconomic and racial/ethnic disparities in postsecondary outcomes (N. W. Hillman, 2016; Turley, 2009). This underscores the importance of understanding the mechanisms that link college proximity to college choice. It also underscores the importance of documenting geographic variation in postsecondary outcomes. In other words, why do people tend to enroll in colleges that are close to home, and what does this mean for people who live in areas with low geographic access to higher education?

Potential Mechanisms Linking College Proximity to College Choice

Information. One of the leading explanations for the relationship between college proximity and college choice has to do with information. That is, people may attend colleges that are close to home because it is easier to access information about nearby colleges (Do, 2004; Griffith & Rothstein, 2009). This could be because college recruiters are more likely to visit local high schools than they are to visit high schools that are farther afield. It may also be because, within a given community, there will be a relatively high concentration of local college alumni. In this way, and in line with social capital theory, people’s ideas about their college options may be shaped by their surroundings.

When people live in areas where colleges are few and far between—areas with low levels of geographic access—their access to information about colleges may be especially limited. This could lead them to forgo college altogether, or to enroll in a college that is not a good academic fit for them.

One of the implications of this line of reasoning is that people might make different choices about where to attend college if they had more information about their college options. Many college choice interventions have been motivated by this idea, with mixed results. In their landmark paper, Hoxby and Turner (2013) found that a light-touch informational intervention had a significant, positive impact on selective college enrollment among high-achieving students from low-income backgrounds. However, when a group of researchers from the College Board tested a similar intervention several years later, they came up with a null result (Gurantz et al., 2020). More research is needed to try to make sense of these contradicting findings. One possible explanation is that, thanks to the Internet, it has become easier for students and their families to access information about colleges, whether they are nearby or farther away.

Social Ties. Social ties may also help to explain the relationship between college proximity and college choice. In other words, people may attend nearby colleges because they want, or need, to stay close to family and friends (Desmond & Turley, 2009; Goldrick-Rab, 2017; Núñez & Bowers, 2011; Ovink & Kalogrides, 2015; Turley, 2009). People's desire to stay close to home may be shaped by cultural norms. For example, Desmond and Turley (2009), argue that the cultural norm of familism—prioritizing the family over the individual—can help to explain why, in a survey of Texas high school students, Hispanic students were more likely than White students to report a desire to live at home during college. In addition to cultural norms, family circumstances may influence people's decisions. For example, some people may attend college close to home so they can continue to look after their younger siblings while their parents or guardians are at work (Goldrick-Rab, 2017, p. 153).

For those who live in areas with low geographic access to higher education, the need to stay close to home may dissuade them from attending college altogether. Alternatively, it could lead them to enroll in the closest college possible, even if it does not align with their interests and qualifications.

To the extent that people's decisions to attend nearby colleges are shaped by social ties, informational interventions may not have much of an impact. Financial aid interventions—interventions that make it more affordable to attend a far-away college—may also fall short. Given this, some scholars have argued in favor of increasing funding for under-resourced colleges, rather than trying to encourage students to prioritize academic match over college proximity (N. Hillman & Weichman, 2016; Ovink et al., 2018). The idea here would be to weaken the relationship between college choice and college outcomes, such that students, regardless of where they attend college, could have a high chance of success.

Costs. Finally, many scholars have argued that the relationship between college proximity and college choice can be explained by costs. Here, I am referring to financial costs. If it is more expensive to attend a far-away college, this could help to explain why people tend to attend colleges that are closer to home (Briscoe & De Oliver, 2006; Card, 1995; Dillon & Smith, 2017; Do, 2004; Griffith & Rothstein, 2009; Rhodes, 2021; Spiess & Wrohlich, 2010; Turley, 2009). With the notable exception of out-of-state tuition, however, colleges do not charge higher tuition to students who come from far away. Why, then, might it be more expensive to attend a far-away college? To start, the farther students travel, the less feasible it will be for them to live at home with their parents or guardians.[30] This means their living expenses, in terms of rent, utilities, and meals, may be much higher than they would be otherwise. In addition, depending on how frequently students visit home, they may have higher transportation costs.

If it is more expensive to attend a far-away college, then people with low levels of geographic access may find the costs of college to be especially high, since they have no choice but to attend a college that is relatively far away. This may deter them from attending college in the first place or cause them to accumulate a large amount of student debt. It may also lead them to attend a low-tuition college, regardless of whether it is a good academic fit.

At this point, it is important to acknowledge that colleges specify different "costs of attendance" (COA) for students with different living situations. COAs are meant to capture the full cost of a year of college for a full-time student (including tuition, housing, meals, and school supplies). They are used, along with students' Expected Family Contribution (EFC) from the Free Application for Federal Student Aid (FAFSA), to determine students' eligibility for financial aid (Goldrick-Rab, 2017). At the University of California-Berkeley, for example, the COA for in-state students who live at home was $31,124 in 2022-23. For in-state students living on campus, it was $43,794, roughly $12,000 higher. For in-state students living in an off-campus apartment, it was $39,094 (UC Berkeley, 2022). In some cases, this may mean that students who move away from home will be awarded more grant-based aid. It could also mean that they will have a greater amount of unmet financial need, which could lead them to accumulate more

[30] According to data from the High School Longitudinal Study of 2009, over 40 percent of students live with their parents, guardians, or other relatives during the first year of college (Author's calculations).

student debt. Given this complexity, it is possible—but not inevitable—that students who attend far-away colleges will face higher costs.

Ultimately, if there is a link between college proximity and college costs, this would have important implications for higher education policy. For example, such a finding could be used to justify the provision of additional grant-based aid to those who live in areas with low geographic access. This could reduce these students' distance-related costs, thereby making it easier for them to attend college, and to prioritize factors like academic fit. Alternatively, if there is no link between proximity and cost, this would also have important policy implications. For example, rather than spending scarce resources on supplemental aid to students with low geographic access, it may be more worthwhile to invest in informational interventions, or in efforts to improve the quality of colleges in geographically isolated areas.

The Present Study

Despite the long-recognized importance of college affordability in higher education policy discussions, there has been relatively little research on the relationship between college proximity and college costs or, relatedly, the relationship between geographic access and college costs. Thus, while many scholars have theorized that there is a link between these things, there is little empirical evidence to support this argument. The present study tests the plausibility of this argument by investigating the association between geographic access and student debt accumulation, an important indicator of college costs (Furquim et al., 2017; Houle, 2014).

As discussed above, those who grow up in areas with low levels of geographic access may face higher college costs because they must travel longer distances to attend college. Thus, if there is an association between geographic access and college costs, we should also expect to see an association between (1) geographic access and distance traveled, and (2) distance traveled and college costs.

I assess the plausibility of this line of reasoning by examining the following three research questions:

- RQ1: Do students with lower levels of geographic access travel longer distances to attend college?
- RQ2: Do students who travel longer distances accumulate more student debt?
- RQ3: Do students with lower levels of geographic access accumulate more student debt and, if so, could this be because they travel longer distances?[31]

I hypothesize that, after accounting for potential confounding factors, students with lower levels of geographic access will travel longer distances, and that students who travel longer distances will accumulate more debt. Further, I hypothesize that there will be an association between these things, such that students with lower levels of geographic access will accumulate more debt.

These are relatively straightforward questions. Answering them in a compelling way, however, is challenging. In part, this is because different colleges have different tuition rates. In the public sector, for example, two-year colleges tend to have lower tuition rates than four-year colleges. Given this—and given what we know about the relationship between college proximity and college choice—we would expect someone who lives closer to a two-year college to be more

[31] At first glance, RQ3 may seem redundant. After all, if students with low geographic access tend to travel longer distances, and if students who travel longer distances take on more debt, then shouldn't it also be true that students with low geographic access will take on more debt? This may very well be the case, but it is also possible to imagine a contradictory scenario. For example, perhaps the association between distance and debt is being driven by a subset of high-access students who, for some reason, have an unusually high appetite for distance and debt. RQ3 allows me to rule out this possibility.

likely to attend such a college and, as a result, to have lower college costs than someone who lives closer to a four-year college. This may be noteworthy, but it does not shed light on whether it is more expensive to attend a far-away versus a nearby college. Thus, in the interest of isolating the association between distance and cost, I am mainly interested in comparing people who have *multiple* nearby college options to people whose *only option* is to attend a far-away college. Figure 2.1 summarizes this conceptual model.

Data and Methods

Data

The data for this study come from a variety of sources. The most important of these sources is the High School Longitudinal Study of 2009 (HSLS: 09). HSLS is administered by the National Center for Education Statistics (NCES). It follows a nationally representative sample of people in the U.S. who were enrolled in ninth grade in 2009. Data collection for HSLS is still ongoing, but the most recent follow-up survey was conducted in 2016, approximately three years after most respondents graduated from high school. For this study, I use many variables from the public-use version of HSLS and a handful of variables from the restricted-use version.

There are several reasons why HSLS is the ideal dataset for this project. First, it focuses on a relatively recent cohort of students. This means it reflects recent trends in higher education, including rising college-going rates, rising tuition rates, and rising student debt loads. Second, HSLS contains in-depth information on respondents' background characteristics, as well as their experiences in high school and college. Importantly, for the purposes of this study, HSLS contains data on where respondents attended high school and college, as well as data on the amount of debt they accumulated during their first year of college. For more information about HSLS, refer to Chen (2020).

In addition to HSLS, I use data from a variety of administrative sources, all of which are publicly available. These data allow me to measure students' level of geographic access, as well as the distance they travel to attend college. I use data from the Common Core of Data (CCD) and the Private School Universe Survey (PSS) to obtain information about the location of HSLS respondents' high schools. I use data from the Integrated Postsecondary Education Data System (IPEDS) to obtain information about the colleges near respondents' high schools, and about respondents' first colleges. Because most HSLS respondents started their senior year of high school in the fall of 2012, I use data from the 2012 versions of the CCD, PSS, IPEDS. Finally, I use the Zip Code Distance Database from the National Bureau for Economic Research (NBER) to compute the distance between high schools and colleges. Briefly, the Zip Code Distance Database is a database that contains every zip code combination in the U.S., and the distance between those zip codes (NBER, n.d.).

Sample

In this study, I focus on on-time high school graduates who enroll in college immediately after high school. Therefore, I restrict my analytic sample to HSLS respondents who graduated from high school in 2013, and who were enrolled in college as of November 2013. Also, because I use variables from the 2009, 2012, and 2013 survey waves, I restrict my sample to those who responded to all three of these waves. Finally, due to idiosyncrasies in the way that Alaska, Indiana and Vermont report their community college data to IPEDS, I exclude respondents who attended high school in these three states.[32] This yields an unweighted sample size of 9,000. With the appropriate weights, the sample size is 2,178,330.[33]

Variables

This study focuses on the associations between three key variables: geographic access to higher education, distance traveled to college, and student debt. Below, I describe each of these variables in detail. I also describe my control variables and weighting strategy. Table A2.1 in the Appendix includes a detailed description of all the variables I use in this study.

Geographic Access to Higher Education. From a conceptual standpoint, geographic access to higher education is relatively straightforward: some people live near an abundance of colleges, while others do not. That said, there are many ways to measure geographic access. Some studies measure geographic access by looking at the distance between a person's hometown and the nearest college. For example, in their paper on the impact of attending a two-year college on degree completion outcomes, Long and Kurlaender (2009) use distance to the

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[32] In IPEDS, most colleges with full-scale campuses are reported as individual entities—each college has its own unique identifier, its own zip code, et cetera. This is not the case when it comes to Indiana and Vermont's community colleges. These states' multi-campus community college systems are grouped together under a single IPEDS identifier, with a single zip code. Alaska also deviates from the norm. In this state, there are no stand-alone two-year colleges, but there are three four-year colleges that offer an array of sub-BA credentials. These idiosyncrasies make it challenging to determine Indiana, Vermont, and Alaska residents' proximity to two-year colleges, which makes it challenging to determine their level of geographic access. Thus, I have opted to exclude them from my analysis. This reduces my sample size by approximately 300 respondents. In supplementary analyses (available upon request), I find that excluding these respondents does not have a meaningful impact on my results.

As of 2012, Wisconsin also had a system of two-year colleges, the UW Colleges. Until they were merged with Wisconsin's four-year public colleges in 2019, this system of colleges was reported as a single entity in IPEDS. However, Wisconsin also has a system of public, two-year technical colleges, each of which is reported as a separate entity in IPEDS. Most two-year collegegoers in Wisconsin attend these technical colleges, as opposed to the UW Colleges. For this reason, I do not exclude Wisconsin residents from my analysis.

Refer to the Limitations and Justifications section for more information about the limitations of using IPEDS data for this project.

[33] I round all sample sizes to the nearest ten to comply with NCES data reporting requirements.

nearest two-year and four-year college as an instrument for two-year college attendance. Other studies rely on categorical measures of geographic access. For example, Hillman and Weichman (2016) classify core-based statistical areas and commuting zones as being “education deserts” if they do not contain at least one nonselective, four-year public college.

For this study, because I am interested in comparing people with multiple nearby college options to people with no nearby college options, I use a categorical measure of geographic access. My primary measure is a county-based measure. Specifically, I classify respondents as “high access” if they are from a county with at least one public four-year and one public two-year college. I classify respondents as “four-year only” if they are from a county with at least one public four-year, but no public two-year college. I classify respondents as “two-year only” if they are from a county with at least one public two-year, but no public four-year college. Finally, if respondents are from a county with neither type of college, I classify them as “low access.” Refer to Figure 2.2 for a visual representation of this classification scheme.

In supplemental analyses, I test the robustness of my findings by using a radius-based measure of geographic access. This measure is similar to the county-based measure, but instead of focusing on the colleges in students’ home counties, it focuses on the colleges that are located within a 30-mile radius of their hometowns. I opted for a 30-mile radius for this measure because it comes close to the median distance that respondents in my analytic sample traveled to attend college.

Like Hillman and Weichman (2016), I exclude private colleges from my measure of geographic access. This is for two reasons. First, private colleges tend to enroll fewer students than public colleges. Second, private colleges tend to have higher tuition rates. These factors make private colleges less accessible than public colleges and, thus, less relevant to a measure of geographic access. In addition, I exclude highly selective colleges (i.e., those that admit fewer than 50 percent of applicants) because these are less accessible to the average student. I also exclude colleges with less than 500 full-time-equivalent undergraduate students, colleges with no in-person instruction, and colleges located outside of the 50 U.S. states. If a college has multiple campus locations (e.g., a main campus and a branch campus) but is reported to IPEDS under a single ID number, I count it as a single institution.[34]

Because I do not have access to HSLS respondents' home addresses, I use the location of their most recent high school as a proxy for their hometown. To construct my county-based measure of geographic access, I begin by using data from IPEDS to determine the number of public two-year and four-year colleges in each county in the United States. Using this information, I assign each county to a geographic access category. Next, I merge these data with data from the CCD and PSS, using FIPS county codes as the matching variable. At this point, for each high school in the U.S., I have a variable indicating whether it is in a high-access, four-year-only, two-year-only, or low-access county. The last step in the process is to merge these data with the HSLS data, using the NCES ID of HSLS respondents' most recent high school as the matching variable.

To create the radius-based measure of geographic access, I use a similar procedure. The difference is that, instead of focusing on counties, I focus on the 30-mile radius that surrounds each U.S. zip code. To do this, I merge data from IPEDS with data from NBER's Zip Code

[34] The exception to this rule is when a multi-campus *system* of colleges is reported under a single IPEDS ID number, as is the case with Indiana and Vermont's community college systems. I explain how I deal with these situations in the "Sample" sub-section.

Distance Database. This allows me to determine, for each zip code in the U.S., the minimum distance between that zip code and the nearest public two-year and four-year college. Using these minimum distances, I assign each zip code to a geographic access category. Next, I merge these data with data from CCD and PSS, using zip codes as the matching variable. The last step in the process is to merge these data with the HSLS data, using the NCES ID of HSLS respondents' most recent high school as the matching variable.

Distance Traveled to College. The second key variable for this study is distance traveled, which refers to the distance, in miles, between a respondent's high school and the first college they attend. To create this variable, I use a multi-step procedure, which I summarize in Figure A2.1. Briefly, I begin by gathering data on respondents' high school and college zip codes. Next, I merge these data with the NBER's Zip Code Distance Database. Following that, I manually inspect any non-merged observations to determine why they did not merge. In some cases, this is because the zip codes are more than 1,000 miles apart (the upper bound of my distance measure). In others, it is because one of the zip codes is not included in the Zip Code Distance Database. In these cases, I replace the unmatched zip code with the closest alternative zip code.[35] I then re-merge the high school and college zip codes with the Zip Code Distance Database. Finally, I confirm that all remaining non-merged observations are due to the zip codes being more than 1,000 miles apart, and I top-code these observations with a value of 1,000. I also assign these observations a top-code flag, which I include in my regression models.

[35] The Zip Code Distance Database excludes so-called "unique" zip codes—zip codes that are used to route mail to special, high-volume addresses. Because many colleges, and some high schools, use unique zip codes, it is somewhat common for non-merges to occur for this reason. In these cases, I substitute the "unique" zip code with the closest non-unique zip code, using a zip code mapping website (UnitedStatesZipCodes.org, n.d.).

Another thing to note about the Zip Code Distance Database is that it measures straight-line distances. In colloquial terms, one would say it measures distance "as the crow flies."[36] This means that my measure of distance does not take roads, mountains, or bodies of water into account. To determine whether this might cause any significant issues from a validity standpoint, I drew a random sample of 40 people from my dataset and I used Google Maps to measure the distance between their high school and college zip codes. As expected, the distances from Google Maps were slightly longer than the distances I computed using NBER's Zip Code Distance Database, as it is rare for there to be a perfectly straight road between two points. That said, the correlation between the two measures was 0.98. I argue that this provides sufficient evidence to support the validity of my measure.

Student Debt. I focus on student debt accumulation during the first year of college.[37] There are several different types of student loans for undergraduates, including federal loans that are issued to directly to students, federal loans that are issued to parents, and private loans. For the purposes of this study, I focus on federal loans that are issued directly to students. These include Stafford and Perkins loans. I do not include private loans because HSLS does not contain information about these. I also do not include parent loans (i.e., Direct PLUS loans) because parents have a variety of options when it comes to financing their children's education. Direct

[36] According to the NBER website, "ZIP Code Distances are great-circle distances calculated using the Haversine formula based on internal points in the geographic area" (NBER, n.d.).

[37] My decision to focus first-year debt loads, as opposed to cumulative debt loads, was motivated by my desire to mitigate the potential for selection bias. Because geographic access could be related to persistence (lower access, less persistence), and persistence could be related to student debt (more persistence, more debt), focusing on cumulative debt loads could lead me to underestimate the association between geographic access and student debt.

PLUS loans are one option, but there are many others (Zaloom, 2019). Given this complexity, I focus on loans that are issued directly to students.

I obtain the data for my student debt variable from the National Student Loan Data System (NSLDS) file in the restricted-use HSLS data. This file contains information on the type, amount, and origination date of every federal loan that has been issued to HSLS respondents since they began college (up until 2016, the most recent wave of HSLS data collection). When I construct my student debt variable, I include every Stafford and Perkins loan that is classified as a "first-year undergraduate" loan, and that was issued between July 1 of 2013 and June 30 of 2014. If respondents did not take out any loans that met these criteria, I assign them a value of 0.

In some analyses, I use a binary indicator of student debt (1=took out student loans, 0=did not take out student loans). In other analyses, I use a continuous indicator of student debt, equal to the dollar amount of federal student loans that students accumulated during their first year of college.

My decision to focus on student debt, as opposed to some other indicator of college costs, was a pragmatic one. Although student debt is not a comprehensive indicator of the costs of college, it is something that it possible to measure using the HSLS data. It is also a very policy-relevant measure, as it is something that can have a significant impact on people's lives after college. Indeed, scholars have found that student debt can cause people to delay or forgo important life milestones like marriage (Gicheva, 2016), homeownership (Mezza et al., 2019), and childbearing (Kuperberg & Mazelis, 2022). It can also influence people's decisions about where to live (Tabit & Winters, 2019) and which types of careers to pursue (Minicozzi, 2005; Rothstein & Rouse, 2011). Given all of this, I argue that, in the absence of a comprehensive measure of college costs, student debt is an acceptable alternative. Future research should gather more detailed data on students' expenses, which could be used to generate more precise measurements of the association between geographic access and college costs.

Control Variables. To minimize bias and maximize the precision of my estimates, I use the following control variables in my regression models: gender, race/ethnicity, socioeconomic status, family structure, Census region, and high school GPA. I selected these variables after reviewing the empirical and theorical literature on geographic inequality, college choice, and student debt. This review helped me to identify factors that could lead me to misestimate the associations between geographic access, distance traveled, and student debt. For example, if I observe that people from low-access areas tend to take on more student debt, this could be because they face higher college costs. Alternatively, it could be because, in low-access areas, there is a relatively high proportion of people from lower SES backgrounds. If this is the case, then failing to control for SES in my regression models could lead me to overestimate the association between geographic access and student debt, as people from lower SES backgrounds are more likely to take on student debt (Houle, 2014).

In addition, in some of my regression models, I control for the sector and control of respondents' first college (i.e., whether respondents attended a two-year or four-year institution, and whether that institution was public, private, or for-profit). Arguably, this is an "intermediate" or "downstream" outcome, in that it may be influenced by geographic access. This means that including it my regression models could introduce selection bias into my estimates (Angrist & Pischke, 2009, pp. 64–68). Nevertheless, I include college type in some of my models to test the robustness of my findings (e.g., holding college type constant, are there still important differences between people with higher and lower levels of geographic access?).

Weights. All my analyses use the appropriate weighting variables to account for the complex sampling design of the HSLS survey, as well as attrition across survey waves. Because my analyses include variables from the 2009, 2012, and 2013 survey waves, I use the W3W1W2STU weights. These weights restrict my analysis to those who participated in all three survey waves, while at the same time adjusting my estimates so they are nationally representative. Recall that my analytic sample is restricted to on-time high school graduates who were enrolled in college as of November 2013, and who did not attend high school in Alaska, Indiana, or Vermont. This means that, when the appropriate weights are applied, my findings can be interpreted as representative of people in the U.S. who were in ninth grade in 2009, and who meet my sampling criteria.

Analytic Strategy

The Association Between Geographic Access and Distance Traveled (RQ1). In the first part of my analysis, I investigate the association between geographic access and distance traveled to college. To do this, I use ordinary least squares (OLS) regression. The basic OLS model for this part of my analysis can be expressed as follows:

$$\mathrm{LN}(DISTANCE) = \beta_0 + \beta_{1-3}ACCESS + \beta_4 X + \varepsilon, \tag{1}$$

where LN(DISTANCE) is the natural log of the distance between a respondent's high school and the first college they attend, ACCESS is a series of dummy variables indicating respondents' level of geographic access to higher education, X is a vector of control variables, and ε is a person-level error term. My decision to log-transform the distance traveled variable was informed by preliminary descriptive analyses. These analyses lent support to the idea that the association between college proximity and distance traveled was linear in logs.

The Association Between Distance Traveled and Student Debt (RQ2). In the second part of my analysis, I examine the association between distance traveled and student debt. Student debt can be a challenging variable to analyze. This is because many people do not accumulate any student debt, especially during the first year of college. Indeed, in my analytic sample, 61 percent of students borrow zero dollars during their first year of college. The remaining 39 percent borrow a non-zero amount. This makes student debt a limited dependent variable (LDV), a variable that is "continuously distributed over a range of values" but has a significant mass of observations at a particular value (in this case, $0) (Wooldridge, 2010, p. 668). Other examples of LDVs include hours worked and healthcare expenditures.

There are conflicting perspectives about the best way to model LDVs. Angrist and Pischke (2009) argue that OLS regression can be used to estimate "effects on averages" (p. 101). Thus, if one is interested in the extent to which average loan amounts vary across people who travel shorter or longer distances to attend college, a traditional OLS regression model would be an appropriate choice. This model would include people with zero as well as non-zero debt. Of course, when dealing with an LDV, effects on averages may not be the only parameter of interest. One may also be interested in in "distribution effects" (e.g., whether people who traveled longer distances had a higher *likelihood* of taking on debt). In this case, Angrist and Pischke recommend converting the LDV into a dichotomous variable and analyzing it using a linear probability model (ibid, p. 101).[38]

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[38] A logit or a probit model would also be appropriate in this case.

Other scholars argue that using OLS regression to analyze an LDV is not ideal, as it will fail to capture the "qualitative difference between limit (zero) observations and nonlimit (continuous) observations" (Greene, 2003, p. 762, as cited by Rodriguez et al., 2018). As an alternative, these scholars recommend using a two-part regression model, also known as a double-hurdle regression model (Cragg, 1971; Rodriguez et al., 2018, p. 39). In the case of student debt, the first part of the model would estimate the *likelihood* of taking on debt. The second part would estimate the *amount* of money people borrowed, *conditional* upon having borrowed a non-zero amount. Typically, researchers use a probit model for the first part and a truncated regression model for the second part (Furquim et al., 2017; Houle, 2014; Rhodes, 2021; Rodriguez et al., 2018).[39]

Two-part models have become a popular choice among those who study student debt. They have been used to analyze debt disparities by income (Houle, 2014), parental education (Furquim et al., 2017), and locale (Rhodes, 2021). That said, some have argued that the second part of these models is likely to suffer from selection bias (Angrist & Pischke, 2009, p. 99).[40]

Given these conflicting perspectives, I use a three-pronged strategy to answer my second research question. First, following the suggestion of both groups of researchers, I estimate the

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[39] A truncated regression model adjusts the distribution of the error terms so they have a "truncated normal distribution, which is a normal distribution that has been scaled upward so that the distribution integrates to one over the restricted range" (Stata, n.d.).
[40] To understand why, imagine a student debt experiment. In this experiment, the treatment condition reduces a person's likelihood of taking on student debt. As a result, the *composition* of people with non-zero debt is going to vary by condition, possibly in ways that are not observable. Thus, if we restrict our analysis to those with non-zero debt, our estimates of the effect of treatment (x) on student debt (y) may suffer from selection bias. The same logic would apply in a non-experimental setting; if distance traveled is associated with a person's likelihood of taking on debt, examining the association between distance traveled and student debt, conditional upon having non-zero debt, may be problematic.

association between distance traveled and the likelihood of taking on student debt. For ease of interpretability, I do this using a linear probability model (LPM), which can be expressed as follows:

$$\mathrm{PR}(DEBT) = \beta_0 + \beta_{1-4} DISTANCE + \beta_5 X + \varepsilon, \tag{2}$$

where PR(DEBT) is a binary indicator of whether the respondent had first-year debt; DISTANCE is a series of dummy variables indicating whether respondents were in the first, second, third, fourth, or fifth quintile in terms of "distance traveled"; X is a vector of control variables; and ε is a person-level error term. My decision to convert the distance traveled variable into quintiles was informed by preliminary descriptive analyses. These analyses lent support to the idea that the association between distance traveled and student debt was non-linear. That said, in supplemental analyses, when I use a continuous version of distance traveled (i.e., logged distance traveled), I obtain similar results.[41]

Second, following the suggestion of Angrist and Pischke (2009), I use OLS regression to estimate the association between distance traveled and logged student debt. This model can be expressed as follows:

$$LN(DEBT) = \beta_0 + \beta_{1-4} DISTANCE + \beta_5 X + \varepsilon, \tag{3}$$

where LN(DEBT) is the natural log of the amount of debt students accumulate during their first year of college, and the rest of the terms are identical to those in Equation 2. My decision to log-transform the student debt variable was informed by preliminary descriptive analyses, which indicated that this would be beneficial, from a model-fitting perspective.[42]

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[41] Results from these supplemental analyses are available upon request.
[42] Before log transforming the variable, I added 1 to every observation, so that respondents with a value of 0 could still be included in my analysis. (Recall that the log of 0 is undefined.)

Third, following the suggestion of Rodriguez et al. (2018) and others, I use truncated regression to estimate the association between distance traveled and logged student debt, conditional upon having non-zero debt. This model can be expressed as follows:

$$\mathrm{LN}(DEBT \mid DEBT > 0) = \beta_0 + \beta_{1-4}DISTANCE + \beta_5 X + \varepsilon, \tag{4}$$

where LN(DEBT | DEBT >0) is the natural log of the amount of debt students accumulate during their first year of college, conditional upon accumulating a non-zero amount, and the rest of the terms are identical to those in Equation 2.

The Association Between Geographic Access and Student Debt (RQ3). In the third part of my analysis, I examine the association between geographic access and student debt. To do this, I use a similar strategy as the one I use to answer RQ2. The primary difference is that, instead of distance traveled, I use geographic access as the independent variable of interest. In a final set of models, I add distance traveled as a covariate to examine whether it might help to explain whatever association I observe between geographic access and student debt.

Variation by Socioeconomic Status. The associations between geographic access, distance traveled, and student debt may vary by socioeconomic status. For example, it is possible that the association between geographic access and distance traveled will be especially strong for those from lower SES backgrounds. This might be the case if students from higher SES backgrounds, regardless of geographic access, tend to enroll in far-away colleges, while students from lower SES backgrounds only travel long distances if it is “necessary” for them to do so (i.e., if they live in an area with low geographic access). For this reason, in Part 1 and Part 3 of my analysis, I explore whether there are any significant interactions between geographic access and SES. In addition, in Part 2 of my analysis, I explore whether there is a significant interaction between distance traveled and SES. As I indicate in Table A2.1, my measure of SES is based on the income, education, and occupational status of respondents' parents or guardians. It is standardized to have a mean of 0 and a standard deviation of 1.

Limitations and Justifications

This study has several limitations to bear in mind. First, it is important to remember that my analytic sample does not include people with a gap between high school and college. In large part, this is due to data limitations.[43] Future research, perhaps using data from NCES's Beginning Postsecondary Students (BPS) survey, should investigate whether there are important differences between those who take a gap year (or years) and those who do not. My analytic sample also does not include people who never enrolled in college. This is because the outcome variables for this study are distance traveled and student debt, neither of which are possible to observe for those who never enroll in college.[44] For these reasons, I am careful to emphasize that my results are only generalizable to on-time high school graduates who enroll in college immediately after high school.

Second, I acknowledge that there are many ways to measure things like geographic access, distance traveled, and college costs. This is one of the reasons why I use two different measures of geographic access in my analysis. Still, these measures are only as accurate as the

[43] My sample excludes people with a gap between high school and college because I use data from the 2013 wave of the HSLS survey to determine whether and where students enrolled in college. An alternative source of information about college enrollment patterns is the Student Records (SR) data file. The SR data file contains administrative data from HSLS respondents' colleges, and it includes people who had a gap between high school and college. However, of the 3,271 institutions that were asked to submit SR data, only 1,991 (61 percent) provided this data (Duprey et al., 2020). Thus, had I relied on the SR data instead of the survey data, my sample size would have been much smaller. For more information, refer to Duprey et al. (2020).

[44] If it is true that people with low geographic access tend to incur higher college costs, there may be a population of people who decide not to attend college at all because they suffer from low geographic access and thus would face high costs to attend college.

data that underly them. Though I have done my best to account for idiosyncrasies in my data, it is possible that other idiosyncrasies remain, and that these could affect my results. One of the limitations of my measure of distance traveled is that it does not account for the ease with which people can travel a given distance. This is something that is likely to vary by region and locale. It may also vary by socioeconomic status, as people from higher SES backgrounds are more likely to have access to a personal vehicle. Regarding college costs, as I have already noted, student debt is an incomplete measure of cost.

Third, it is important to remember that this is a descriptive analysis. This project can pave the way for future work that uses causal research designs, but, on its own, it cannot be used to make a causal argument about the relationship between geographic access, distance traveled, and college costs. As I articulate throughout, I do my best to control for potential confounding factors, but ultimately, my findings could suffer from omitted variables bias.[45]

Results

Descriptive Statistics

Table 2.1 presents descriptive statistics for the full analytic sample and for each of the county-based geographic access categories. All the statistics in this table, and elsewhere in this

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[45] In the preliminary phases of this project, I contemplated the feasibility of a causal research design. Specifically, following the example of other college proximity studies, I considered an instrumental variables (IV) design. For this project, distance from the nearest two-year and four-year college (Z) could be used to predict distance traveled (X), which could be used to predict student debt (Y). See Figure A2.2 in the Appendix for a diagram of this set-up. The goal with this design would be to obtain an unbiased local average treatment effect (LATE) of distance traveled on student debt, for those whose travel distance was affected by their proximity to two-year and four-year colleges. The problem with set-up is that it does not satisfy the exclusion restriction for an IV research design (Angrist & Pischke, 2009, pp. 116–117). The exclusion restriction states that Z (the instrument) can only affect Y (the outcome) via X (the predictor variable of interest). In this case, the exclusion restriction is violated because college proximity, in addition to influencing travel distance, can also affect the type of college a person attends, which can affect the amount of debt they take on. For this reason, I do not use an IV strategy for this project.

paper, were computed using the appropriate survey weights. Focusing on the full analytic sample, 40.5 percent of the sample is in the high-access category and 18.3 percent is in the low-access category. Most of the rest of the sample is concentrated in the "two-year-only" category, with only 6.3 percent of the sample in the "four-year-only" category. Regarding distance traveled, the mean is 125.6 miles. The median distance traveled (not shown) is 31 miles. These two pieces of information indicate that the distance traveled variable is right skewed, which is confirmed by the histogram in Figure 2.3. Regarding student debt, 39 percent of respondents took on first-year student loans.[46] The average first-year loan amount, including those with zero loans, is roughly $2,100. Refer to Figure 2.4 for a histogram that shows the distribution of the student debt variable.

In terms of sociodemographic characteristics, the analytic sample for this study differs slightly from the original sample of HSLS respondents, as described by Ingels et al. (2009, p. 5). For example, 53.9 percent of the analytic sample is female, compared to 50.2 percent of the original sample. In addition, 54.8 percent of the analytic sample identifies as White and 12.2 percent identifies as Black or African American, compared to 51.2 percent and 13.8 percent of the original sample. These differences reflect broader national trends in college enrollment. Nationally, among recent high school graduates, females have higher enrollment rates than males (National Center for Education Statistics, 2021b) and those who identify as White have higher

[46] This may seem low, given that roughly two-thirds of BA graduates leave college with student loans (Thomsen et al., 2020, p. 73). However, it may simply mean that students' likelihood of taking out loans increases in the later years of college. This makes sense, given that financial aid packages tend to be the most generous during the first year of college (Goldrick-Rab, 2017) and given that families' college savings may become depleted over time.

enrollment rates than those who identify as Black or African American (National Center for Education Statistics, 2021a).

Focusing on low-access versus high-access students, there are some important differences in terms of distance traveled and student debt. Starting with distance traveled, low-access students have a lower mean than their high-access counterparts—111.2 versus 134.4 miles. That said, there is a greater share of low-access students with "above-median" travel distances. Indeed, 63.3 percent of low-access students travel more than 31 miles, compared to 44.2 percent of their high-access counterparts. This suggests that, in the low-access category, there is a relatively small share of people who travel very long distances, but also a relatively small share of people who travel very short distances. Turning to student debt, 42.5 percent of low-access respondents took out a loan during their first year of college, compared to 37.5 percent of high-access respondents. The average debt load, including zeros, for low-access respondents was $2,326, compared to $2,057 for high-access respondents.

There are also some important sociodemographic differences between the low-access and high-access categories. Notably, the low-access category has a relatively high proportion of White respondents (69 percent, versus 42.3 percent for the high-access category) and a relatively low proportion of Hispanic respondents (10.1 percent, versus 27.1 percent for the high-access category). There are also some sizable differences in terms of region. Specifically, the low-access category has a higher share of students from the South and the Midwest, and a smaller share of students from the Northeast and West.

It is also worthwhile to examine how the initial college destinations of HSLS respondents vary by geographic access. In line with the conceptual framework that I outlined in Figure 2.1, students from low-access and high-access backgrounds have similar enrollment patterns—roughly two-thirds enroll in four-year colleges, and roughly one-third enrolls in two-year colleges. That said, there are some differences across the two categories. For example, high-access students are slightly more likely to enroll in four-year private and two-year public colleges, relative to their low-access counterparts. Notably, low-access and high-access students' enrollment patterns stand in stark contract with the enrollment patterns of those from the four-year-only category. As predicted by the literature on college proximity and college choice, students in this category are heavily concentrated at four-year public colleges (61.2 percent enroll in such colleges). The contrast is less stark when it comes to "two-year-only" students, who are only slightly more likely to enroll in two-year public colleges, compared to high-access and low-access students (37.7 percent, versus 35.4 percent and 33 percent, respectively).

Table 2.1 also includes information about respondents' hometown locales. As expected, a disproportionate share of low-access respondents come from towns and rural areas and a disproportionate share of high-access respondents come from cities and suburbs. That said, there are people from cities in the low-access category, and there are people from rural areas in the high-access category. Because locale is highly correlated with geographic access, including it as a control variable in my regression models could result in multicollinearity issues. For this reason, I do not include locale as a covariate in my regression models.

Table A2.2 presents a similar set of descriptive statistics using the radius-based measure of geographic access. One important difference to note is that, according to this measure, over 70 percent of the sample is classified as high access, with only 5 percent being classified as low access. This discrepancy between the county-based and radius-based measure is understandable, given that the size of most counties is smaller than the size of a circle with a 30-mile radius ($\pi * 30^2 = 2{,}827$). Indeed, according to data from the National Historical Geographic Information System, the average land area for a U.S. county is just over 1,100 square miles (Manson et al., 2022). What this means is that, with the radius-based measure, the threshold for being classified as low access is higher, while the threshold for being classified as high access is lower.

Regression Results

Geographic Access and Distance Traveled (RQ1). Table 2.2 presents selected results from a series of OLS regression models that examine the association between geographic access and logged distance traveled.[47] Recall that I use a logged version of distance traveled because, in preliminary descriptive analyses, I determined that the association between geographic access and distance traveled was linear in logs.[48] These models use the county-based measure of geographic access, with "high access" serving as the reference category. The first model does not include any control variables. The second model controls for respondents' sociodemographic characteristics and academic qualifications. The third model includes a categorical variable indicating the level and control of respondents' first college.

Across all three models, the coefficient for "low access" hovers between 0.53 and 0.57 and is statistically significant at the $p<0.001$ level. Using the standard rule of thumb for interpreting coefficients from a regression model with a logged outcome variable, this means that low-access students travel approximately 50 percent farther, on average, than their high-access counterparts. More precisely, using the coefficient from Model 2, we can say that low-access

[47] For the full set of regression results from these models, refer to Table A2.3.

[48] I determined this by plotting the association between distance to the nearest four-year college and distance traveled, as well as the association between distance to the nearest two-year college and distance traveled.

students travel 70.6 percent farther, on average, than their high-access counterparts (100*[$e^{0.534}$-1] = 70.57). Across all three models, the coefficients for "four-year only" and "two-year only" are small and statistically insignificant. This suggests that the main difference, when it comes to geographic access and distance traveled, is between low-access and non-low-access respondents.

Results from the models that use the radius-based measure of geographic access are similar in terms of direction and significance, but larger in terms of magnitude. Specifically, according to the model that controls for sociodemographic characteristics and academic qualifications, low-access respondents travel nearly two times farther than their high-access counterparts (100*[$e^{1.037}$-1] = 182.07). Refer to Table A2.4 for more details.

Results from the models that examine the interaction between the county-based measure of geographic access and socioeconomic status are presented in Table A2.5. These results show that there is a negative interaction between SES and the dummy indicator for low access (b=-0.340, p<0.001). What this means is that there is a larger "distance traveled" gap between low- and high-access students from low-SES backgrounds than there is between low- and high-access students from high-SES backgrounds. This aligns with the idea that, for students from lower SES backgrounds, the decision to attend a far-away college may be driven by necessity, as opposed to students' preferences.

Distance Traveled and Student Debt (RQ2). Table 2.3 presents selected results from a series of regression models that examine the association between distance traveled and student debt.[49] These models use a categorical indicator of distance traveled because, in preliminary descriptive analyses, I determined that the association between distance traveled and student debt

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[49] For the full set of regression results from these models, refer to Table A2.6.

was not linear.[50] As indicated in Table 2.3, the reference category for these models is the first quintile of distance traveled, which corresponds to people who traveled between 0 and 8 miles to get to their first college. The upper bounds of the second through fifth quintiles are 18, 55, 154, and 1000 miles, respectively.

The first three models in Table 2.3 are linear probability models (LPMs). They examine whether respondents who travel farther have a higher likelihood of taking on first-year student loans. When multiplied by 100, coefficients from a linear probability model can be interpreted as percentage-point changes in the likelihood of a positive outcome. Thus, according to Model 2, respondents in the third quintile are approximately 17 percentage points more likely to accumulate first-year student debt than their first-quintile counterparts, after controlling for sociodemographic characteristics and academic qualifications (p<0.001). Similarly, respondents in the fourth and fifth quintiles are approximately 30 percentage points more likely to accumulate first-year debt than their first-quintile counterparts (p<0.001). Turning to Model 3, we can see that controlling for college type reduces the magnitude of these coefficients by about one-half. This indicates that, to some extent, people who travel farther tend to enroll in more expensive colleges, and people who stay close to home tend to enroll in less expensive colleges. Still, even after controlling for college type, respondents in the upper quintiles are roughly 8 to 20 percentage points more likely to accumulate first-year loans than their first-quintile counterparts (p<0.001).

[50] After experimenting with a decile-based measure, I concluded that a quintile-based measure would fit the data equally well, and in a more parsimonious fashion.

The second group of models in Table 2.3 are conventional OLS regression models. They examine whether students who travel farther have higher average debt loads. Recall that these models include those with zero as well as non-zero debt. In addition, the student debt variable is log-transformed.[51] Similar to the LPM models, the results from these models indicate that students in the upper quintiles of distance traveled have higher average debt loads than their first-quintile counterparts ($p<0.001$). For example, according to Model 5, the average debt load for respondents in third quintile is more than three times higher than the average debt load for respondents in the first quintile ($100*[e^{1.540}-1] = 366.50$).

Results from the truncated regression models, which examine the association between distance traveled and logged student debt for those with non-zero debt, are presented in Table A2.7. These results are consistent with the LPM and OLS results in terms of direction and statistical significance. In terms of magnitude, the coefficients from the truncated regression models are smaller than the coefficients from the standard OLS regression models. This suggests that the OLS results are being driven, for the most part, by differences in the likelihood of taking on debt, rather than differences in loan amounts.

Results from the models that examine the interaction between distance traveled and socioeconomic status are presented in Table A2.8. These results show that, for the fourth and fifth quintiles of distance traveled, there is a negative interaction with SES. What this means is that the association between distance traveled and student debt is stronger for those from lower SES backgrounds than it is for those from higher SES backgrounds. This suggests that traveling

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[51] Before log transforming the variable, I added 1 to every observation, so that respondents with a value of 0 could still be included in my analysis. (Recall that the log of 0 is undefined.)

a long distance to attend college may be more burdensome, from a cost perspective, for students whose families have fewer financial resources.

Geographic Access and Student Debt (RQ3). Table 2.4 presents selected results from a series of regression models that examine the association between geographic access and first-year student debt.[52] The models in Panel A are linear probability models (LPMs). They examine whether students with lower levels of geographic access, according to the county-based measure, have a higher likelihood of taking on first-year loans. According to the first three models in Panel A, respondents in the low-access category are roughly 5 percentage points more likely to accumulate first-year debt than their high-access counterparts. That said, the confidence intervals for these estimates are quite wide, and they fail to meet the conventional level of statistical significance of $p<0.05$. Thus, these results should be interpreted with caution. Turning to Model 4, the coefficient for low access becomes much smaller once distance traveled is added to the model. This suggests that the difference between high-access and low-access respondents may be driven, at least in part, by the fact that low-access respondents tend to travel longer distances. Stated differently, the association between geographic access and student debt may be *mediated* by distance traveled.

The models in Panel B of Table 2.4 are conventional OLS regression models. They examine whether students with lower levels of geographic access have higher average debt loads. Recall that these models include those with zero as well as non-zero debt. In addition, the student debt variable is log-transformed. Consistent with the LPM results, the OLS results indicate that respondents in the low-access category have higher average debt loads than their high-access

[52] For the full set of regression results from these models, refer to Table A2.9.

counterparts. For example, according to Model 7, after controlling for sociodemographic characteristics, academic qualifications, and college type, average amount of debt for those in the low-access category is 51 percent higher than the average amount of debt for those in the high-access category ($100*[e^{0.414}-1] = 51.29$). However, as was the case with the LPM estimates, these coefficients do not reach the conventional level of statistical significance, so they should be interpreted with caution.

Results from the truncated regression models, which examine the association between geographic access and student debt for those with non-zero debt, are presented in Table A2.10. These results indicate that, among those with non-zero debt, there are no significant differences between high-access and low-access respondents.

Results from the models that use a radius-based measure of geographic access are presented in Table A2.11. These results are similar to the main results, in that they provide modest support for the argument that low-access respondents have a higher likelihood of accumulating first-year loans. For example, according to Model 3, low-access respondents are 7.3 percentage points more likely to take on first-year debt, after controlling for sociodemographic characteristics, academic qualifications, and college type ($p<0.05$). As was the case with the county-based models, the coefficient for low access shrinks after controlling for distance traveled. This provides some additional support for the argument that low-access respondents accumulate more student debt because they travel longer distances to attend college.

Results from the models that examine the interaction between geographic access and socioeconomic status are presented in Table A2.12. These results show that the association between geographic access and student debt does not appear to vary by SES. This finding goes against the idea that, for people from lower SES backgrounds, having a low level of geographic access is especially burdensome, from a financial standpoint. That said, it is possible that people from low-access, low-SES backgrounds are facing high financial burdens, but instead of responding to them by taking on more student debt, they are responding to them by attending less expensive colleges or working longer hours for pay. This is something that should be explored in future research.

Discussion and Conclusion

Many scholars have argued that one of the reasons why college proximity matters when it comes to college choice is that it may be more costly to attend a far-away college than it is to attend a college that is close to home (Briscoe & De Oliver, 2006; Card, 1995; Dillon & Smith, 2017; Do, 2004; Griffith & Rothstein, 2009; Rhodes, 2021; Spiess & Wrohlich, 2010; Turley, 2009). One of the implications of this argument is that, when a student's only option is to attend a college that is relatively far away, they may encounter higher college costs, which could lead them to accumulate higher amounts of student debt.

This study assesses the plausibility of this line of reasoning by comparing those who have no choice but to attend a far-away college (i.e., those with a low level of geographic access) to those who have multiple nearby college options (i.e., those with a high level of geographic access). Specifically, I investigate whether those with low geographic access tend to travel longer distances to attend college, and whether this is associated with an increased likelihood of accumulating student debt. Using data from a variety of sources, including nationally representative survey data from HSLS, I find that students with low geographic access tend to travel longer distances to attend college. This is especially true for those from lower SES backgrounds. I also find that students who travel longer distances are more likely to accumulate first-year student loans. Once more, this is especially true for those from lower SES backgrounds. Finally, I find modest support for the argument that students with low geographic access accumulate more student loans, and that this may be driven, in part, by the fact that they travel longer distances to attend college. This last finding should be interpreted with caution, however, as the coefficients are small and, in most cases, fail to reach the conventional level of statistical significance.

Overall, this study offers modest support for the idea that, when it comes to college affordability and student debt, those who live in areas with limited college options may be at a disadvantage. This finding is consistent with the existing research on geographic inequality in higher education, which has identified other important geographic disparities in postsecondary outcomes, including disparities in enrollment, graduation, and labor market outcomes (Card, 1995; Dillon & Smith, 2017; Long & Kurlaender, 2009; Ovink et al., 2018; Shamsuddin, 2016). This study also adds nuance to the existing research on debt disparities between students from rural and non-rural backgrounds (Rhodes, 2021). Specifically, it provides support for the idea that these disparities could be driven by disparities in geographic access to higher education.

In addition, this study offers some support for the "cost hypothesis," as it relates to college proximity and college choice. For years, scholars have theorized that cost can help to explain why people tend to enroll in nearby colleges. However, up to this point, there has been little empirical research on this topic. In this study, although I do not directly investigate the relationship between college proximity and college choice, I do find support for the argument that, broadly speaking, it may be more costly to attend a far-away college. This is demonstrated by my finding that those who travel longer distances to attend college tend to accumulate larger amounts of debt, even after controlling for sociodemographic characteristics, academic preparation, and college type. It is also supported by my suggestive finding that, when people have no other option but to attend a far-away college (i.e., when they have a low level of geographic access), they have a higher likelihood of accumulating student debt.

Of course, there are other possible explanations for these findings. Though I have done my best to account for potential confounding factors, it is possible that unobserved differences between people with higher and lower levels of geographic access have caused me to overestimate the importance of geographic access. For example, in this study, I do not observe people's expected returns to education. If people from low-access areas have especially high expected returns to education, this may help to explain why they are willing to travel farther, and to take on more debt, than their high-access peers. However, given the association between geographic access and rurality, and the fact that college-educated workers in rural areas tend to earn less than their non-rural counterparts (Marré, 2017), this seems unlikely.

In addition, as I highlight in the Data and Methods section, this study has some important limitations to bear in mind. First, because this study focuses on on-time high school graduates who enroll in college immediately after high school, my findings may not be generalizable to those who take shorter—or longer—than four years to graduate from high school, or to those who have a gap between high school and college. Second, it is important to remember that there are many ways to define geographic access, distance traveled, and college costs. For example, although student debt is an interesting and policy-relevant variable, it is not a comprehensive measure of college costs. Future research, using a more detailed measure of college costs, should test the robustness of the findings presented in this paper. Third, it is important to remember that this is a descriptive, as opposed to a causal, study.

Despite these limitations, this study has important implications for future research. First, future research should test the robustness of my finding regarding distance traveled and college costs by gathering more detailed data on the costs students face as they make their way through college, and by examining whether these costs vary by distance traveled. This would address one of the main limitations of this study, which is my reliance on student debt as an indicator of college costs.

Scholars should also look for ways to assess the causal link between distance and cost, and how this might affect students' choices about where to attend college. For example, scholars could investigate whether supplemental financial aid could help to reduce debt disparities between students from low-access and high-access areas. Similarly, scholars who are interested in improving academic match could investigate whether factoring distance-related costs into financial aid packages could make it easier for students to prioritize academic match, especially when they live far away from the nearest match college.

In this time of rising college costs and growing concerns about student debt (Goldrick-Rab, 2017; Zaloom, 2019), it is important to understand who is most affected by these issues, and why. Up to this point, much of the research on this topic has focused on socioeconomic and racial/ethnic inequalities in student debt (Furquim et al., 2017; Houle, 2014). In this study, I build on this line of research by focusing on another, potentially overlapping, dimension of inequality: geographic inequality. I find suggestive evidence that, for those who live in areas with limited college options, the costs of college may be especially high. I also find that, broadly speaking, it may be more costly to attend a far-away college. These descriptive insights pave the way for future research on this topic. Additional research in this area could be one of the keys to understanding, and ultimately remedying, geographic, socioeconomic, and racial/ethnic inequalities in postsecondary outcomes.

Study 3: Higher Selectivity, Higher Engagement? Documenting Variation in College Students' First-year Experiences

In the U.S., selective colleges have several advantages over their less selective counterparts, including more financial resources and higher retention and graduation rates (Bound et al., 2010; Bowen et al., 2009; Hoxby & Avery, 2013; Shamsuddin, 2016). For students from low-income, first-generation, and minoritized backgrounds, the benefits of attending a selective college, in terms of degree completion and labor market outcomes, may be especially large (Alon & Tienda, 2005; Bleemer, 2020; Card, 1995). At the same time, there is evidence that selective colleges can be socially isolating and difficult to navigate for students from these backgrounds (Armstrong & Hamilton, 2013; Jack, 2019; S. E. Johnson et al., 2011). This raises an important, but unanswered question: when students from low-income, first-generation, and minoritized backgrounds attend less selective colleges—colleges with more diverse student bodies, but fewer financial resources—do they have a more positive college experience?

This descriptive study uses survey data from the 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17) to examine this question. Specifically, I ask whether there is an association between college selectivity and student engagement during the first year of college, and whether this association varies by racial/ethnic and socioeconomic background. I focus on student engagement because I am interested in students' perceptions of, and interactions with, their educational environments. Following Ackert (2018), I examine two dimensions of student engagement: affective engagement (feeling emotionally and socially connected to school) and behavioral engagement (engaging in schooling-related activities). I focus on the first year of college because students' experiences during the first year of college can set the tone for the remainder of their postsecondary careers (Barefoot et al., 2004; Phillips et al., 2020; Ribera et al., 2017; Tinto, 1999, 2012).

Using a combination of descriptive statistics and multivariate regression models, I find that, by and large, students at more selective colleges report higher levels of both affective and behavioral engagement. In other words, for most subgroups, there is a positive association between selectivity and engagement, even after accounting for potential confounding factors. However, the strength of this association varies depending on the type of engagement that is being examined, as well as the subgroup that is being analyzed. For example, for most racial/ethnic and socioeconomic subgroups, there is a positive association between selectivity and affective engagement. However, for Black students, this association is relatively flat.

Findings from this study lend additional support to the argument that selective colleges, though far from perfect, have important advantages over their less selective counterparts. Given this, I argue that this study does *not* offer support for the argument that, for some students, there may be significant drawbacks to attending a selective college. This has implications for ongoing debates about college choice, including debates about the extent to which prospective college students should prioritize things like selectivity and prestige during the college search process. That said, more research is needed to fully understand the link between college selectivity and student engagement, as well as the link between college selectivity and other indicators of student wellbeing.

The remainder of this paper proceeds as follows. I begin by situating this project within the existing research on college selectivity and student engagement, and by discussing how institutional resources and student body composition—college characteristics that are closely intertwined with college selectivity—could be connected to student engagement. Next, I describe the data and methods I use for this study. Following that, I present the results from my descriptive analyses and multivariate regression models. I conclude with a discussion of this study's implications for policy, practice, and future research.

Background

Student Engagement in Higher Education

Student engagement is a complex and multi-faceted construct. Broadly speaking, it refers to students' perceptions of, and interactions with, their educational environments (Lawson & Lawson, 2013; National Survey of Student Engagement, 2013). Scholars use the term *affective engagement* to describe students' social and emotional attachments to their educational environments. If a student likes their school and feels a strong sense of belonging there, they can be said to have a high level of affective engagement. *Behavioral engagement*, on the other hand, refers to the extent to which students participate in schooling-related activities, such as studying or meeting with an academic advisor. Some scholars have theorized that affective engagement is an important precursor to behavioral engagement, which can lead to other positive outcomes like learning, persistence, and graduation (Ackert, 2018; Lawson & Lawson, 2013). Affective engagement, to the extent that it overlaps with students' sense of belonging, may also be linked to students' mental wellbeing (Gopalan & Brady, 2019).

Much of the research on student engagement has focused on the link between educational environments and student engagement. A key question for this body of research is, what types of environments lead to higher levels of engagement, and for whom? Research on K-12 schools has found that the answer to this question may depend on the type of engagement that is being analyzed. In other words, environments that foster a high level of affective engagement may not necessarily foster a high level of behavioral engagement (Ackert, 2018). Focusing on the postsecondary sector, researchers from the Indiana University Center for Postsecondary Research, using data from the National Survey of Student Engagement (NSSE), have found that most of the variation in student engagement occurs *within* colleges, as opposed to *between* them (National Survey of Student Engagement, 2008). Furthermore, this same group of researchers has argued that college selectivity is not a significant predictor of between-college differences in student engagement (National Survey of Student Engagement, 2014). In making this claim, however, the researchers rely on two relatively narrow indicators of student engagement: student-faculty interactions and students' exposure to "effective teaching practices." Additionally, they do not examine whether there might be an association between selectivity and engagement for some subgroups of students, but not others. Thus, there is still much more to learn when it comes to college selectivity and student engagement.

There are several reasons to delve deeper into the association between college selectivity and student engagement. From a theory-building standpoint, if there is a positive association between selectivity and engagement, this may help to explain why students who attend selective colleges tend to have better graduation and labor market outcomes. From a practical standpoint, investigating the association between selectivity and engagement could yield important insights for those who are interested in reducing inequalities in student engagement, both within and between colleges. It could also yield important insights for students and their families as they navigate the college choice process.

Selectivity and Financial Resources

Generally speaking, more selective colleges in the U.S. tend to have more financial resources than their less selective counterparts (Bound et al., 2010; Dillon & Smith, 2020, p. 775). There are multiple reasons for this, including the fact that more selective colleges tend to receive more funding from state, federal, and philanthropic sources, as well as more donations from alumni. Hoxby and Avery (2013) illustrate the association between college selectivity and financial resources by looking at instructional expenditures. According to the authors' calculations, colleges that were rated "Highly Competitive" by Barron's spent an average of $12,163 per student during the 2009-10 academic year. Colleges that were rated "Very Competitive" and "Less Competitive" spent around $8,300 and $5,300 per student, respectively (Hoxby & Avery, 2013, p. 7).

Some scholars have theorized that schooling environments with greater financial resources may be more likely to foster high levels of engagement (Ackert, 2018). Thinking about the higher education context, when students attend colleges with ample financial resources, they may have more opportunities to interact with faculty, due to smaller class sizes. They may also have more opportunities to interact with peers, due to the greater prevalence of on-campus housing and higher levels of funding for extracurricular activities. In addition, resource-rich colleges may be able to offer more support services, such as tutoring, academic advising, and career advising. Finally, because colleges with ample financial resources are often able to provide higher levels of need-based financial aid (Hoxby & Avery, 2013), students at these institutions may be able to spend more time on academic and extracurricular activities, rather than working to make ends meet. All these things could lead to higher levels of affective and behavioral engagement. Thus, to the extent that resource-rich environments promote higher levels of engagement, we should expect to see a positive association between selectivity and engagement. I call this the "resource hypothesis."

Selectivity and Student Body Composition

One of the limitations of the resource hypothesis is that it does not account for the possibility that other factors, such as student body composition and campus culture, could also have an impact on student engagement. For example, if someone attends a resource-rich college, but they feel socially isolated because their background is underrepresented at that college, this may lead to low affective engagement. This, in turn, could lead to low behavioral engagement.

The empirical research on this topic, most of which has focused on the K-12 context, offers some support for this line of reasoning. Indeed, several studies have found that students who attend schools with higher proportions of same-race peers report a greater sense of belonging and a greater sense of attachment to their school (Benner & Crosnoe, 2011; M. K. Johnson et al., 2001). Other studies have found that the association between student body composition and student engagement varies depending on the type of engagement that is being examined (i.e., affective versus behavioral). For example, Ackert (2018) finds that, irrespective of race/ethnicity, students at schools with higher proportions of White students exhibit higher levels of behavioral engagement, but lower levels of affective engagement.

Looking to the research on higher education, there is also some support for the idea that student body composition is linked to student engagement. For example, in his in-depth study of a highly selective college with a predominantly high-income student body, sociologist Anthony Jack found that students from low-income backgrounds, especially when they did not have prior exposure to elite schooling environments, struggled to find a sense of community. This made it difficult for them to engage in schooling-related and extracurricular activities, and it took a toll on their mental health (Jack, 2019). In their study of a selective public college, also with a predominately high-income student body, sociologists Elizabeth Armstrong and Laura Hamilton found the college was ill-equipped to meet the needs of students from low-income and first-generation backgrounds. As a result, students from these backgrounds struggled to find their footing, and several of them dropped out or transferred to less selective colleges (Armstrong & Hamilton, 2013). These studies are limited in that they each focus on a single, selective college. That said, they provide some suggestive evidence that, when students from low-income, first-generation, and minoritized backgrounds attend colleges where their background is underrepresented, they may find it more challenging to feel a sense of connection to their college.

To be sure, other factors, such as campus climate, may moderate the association between student body composition and student engagement (Bellmore et al., 2012). In other words, it is possible for a school to have an inclusive campus climate, even if it serves relatively few students from a particular background (Strayhorn, 2019). That said, when a school serves relatively few students from a particular background, campus leaders may find it more difficult to foster a campus climate that is supportive of those students (Solorzano et al., 2000). There may also be few incentives for campus leaders to focus on the wellbeing of students who make up a small share of the overall student body (Armstrong & Hamilton, 2013; Browman & Destin, 2016). Thus, while it is far from inevitable, it is plausible that students, especially when they identify as a member of a historically marginalized group, will feel isolated when they attend schools that serve relatively few students from similar backgrounds.

Compared to their less selective counterparts, more selective colleges in the U.S. tend to serve smaller shares of students from low-income, first-generation, and minoritized backgrounds (Chetty et al., 2017). There are many reasons for this, including systemic inequalities in the K-12 sector and college admissions policies that tend to favor students from higher income backgrounds (Carnevale, 2018; Nichols, 2020; Reeves, 2017). Data from the Integrated Postsecondary Education Data System (IPEDS) can help to illustrate the association between college selectivity and student body composition. According to IPEDS data from 2019, roughly 20 percent of students at the most selective four-year colleges (defined as being in the top 20 percent in terms of admitted students' SAT and ACT scores) received Pell grants. By contrast, nearly 60 percent of students at the least selective four-year colleges received Pell grants.[53,54] The same general pattern applies when looking at the racial/ethnic composition of students at more and less selective colleges. For example, in 2019, 5 percent of students at the most selective four-year colleges identified as Black, compared to 28 percent of students at the least selective four-year colleges.

Considering these patterns, it seems possible, though not inevitable, that students from historically marginalized backgrounds will tend to feel socially isolated at more selective colleges. This could counteract the benefits of attending a college with more resources, leading to a flat or negative association between selectivity and engagement for students from these

[53] Pell grant status is a commonly used, albeit imperfect, proxy for low-income status (Delisle, 2017).
[54] Author's calculations using data from the 2019 IPEDS survey.

backgrounds, but not for their non-marginalized peers. I call this the “social isolation hypothesis.”

The Present Study

Existing research suggests that highly selective colleges have substantial room for improvement when it comes to supporting students from low-income, first-generation, and minoritized backgrounds. At the same time, this research says very little about the experiences of students from similar backgrounds who attend less selective colleges. Do these colleges, with their more diverse student bodies, but fewer financial resources, offer more welcoming and supportive environments?

This descriptive study addresses this question by examining the association between college selectivity and student engagement during the first year of college, and by looking at how this association varies by student background. In so doing, this study evaluates the plausibility of two competing hypotheses: the resource hypothesis and the social isolation hypothesis. According to the resource hypothesis, students who attend better-resourced (i.e., more selective) colleges will experience higher levels of engagement, regardless of background. According to the social isolation hypothesis, the association between selectivity and engagement will be flat or negative for students whose backgrounds are underrepresented at selective colleges, and positive for students whose backgrounds are overrepresented at selective colleges.

Data and Methods

Data

The data for this study come from the base year of the 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17). BPS:12/17 is a nationally representative survey from the National Center for Education Statistics (NCES). It follows students who started college during the 2011-12 academic year for six years after their initial enrollment in college. The survey captures a wide range of data on students' background characteristics, postsecondary trajectories, and, if applicable, their post-college labor market outcomes.[55]

BPS:12/17 is the ideal dataset for this study because it follows students from a wide range of socioeconomic and racial/ethnic backgrounds who attend a wide range of colleges. It is also ideal because it follows a relatively recent cohort of students, which means it reflects recent trends in higher education, including rising college-going rates among students from low-income, first-generation, and minoritized backgrounds. In addition, although previous iterations of the BPS survey have gathered data on students' schooling-related activities (i.e., behavioral engagement), BPS:12/17 is the first to gather data on the extent to which students feel socially and emotionally connected to their college (i.e., affective engagement).

To obtain information about the selectivity, size, and control of BPS respondents' colleges, I merge the BPS:12/17 data with data from the Integrated Postsecondary Education Data System (IPEDS).

Sample

This study focuses on the association between college selectivity and student engagement during the first year of college. Because college selectivity is a construct that mainly applies to the four-year college sector, the population of interest for this study is four-year college students.

[55] The base-year data for BPS:12/17 come from the 2012 National Postsecondary Student Aid Study (NPSAS:12), another NCES survey. To generate this base-year data, NPSAS administrators used a stratified sampling design to sample colleges, and then another stratified sampling design to sample students within colleges. For more information about the survey's sampling methodology, refer to Bryan et al. (2019).

As I discuss in the Variables subsection, I use a test-score based measure of college selectivity. For this reason, I restrict my main analytic sample to students (1) who began their college careers at four-year colleges and (2) whose colleges reported SAT/ACT data to IPEDS in one or more of the following years: 2011, 2012, or 2013. This yields an unweighted sample of 5,150 (1,226,660, weighted).[56]

Variables

Student Engagement. The two dependent variables of interest for this study are affective engagement and behavioral engagement. I define affective engagement as the extent to which a student feels emotionally and socially connected to their college. I define behavioral engagement as the extent to which a student participates in schooling-related activities.

I measure affective engagement by taking the mean of students' responses to five engagement-related items from the base-year BPS survey. These items, which were adapted from NSSE (D. Richards, personal communication, January 25, 2023), ask students to rate their agreement with the following five statements on a scale of 1 (strongly disagree) to 5 (strongly agree):

- "My interactions with my teachers at [college] are more positive than negative."
- "I'm satisfied with my studies at [college]."
- "My interactions with other [college] students are more positive than negative."
- "I'm satisfied with my social experience at [college]."

[56] In supplementary analyses, I use a simple data imputation method to include in my sample students who attended four-year colleges that did not report SAT/ACT score data to IPEDS (n=350). Specifically, I assign these students a median college SAT score of 600 (a low value, reflecting my assumption that most non-score-reporting colleges, especially in the early 2010s, had open-access admissions) and I include a missing data flag in my regression models. These supplementary analyses yield similar results and are available upon request.

- "I feel that I am a part of [college]."

Though these items are grouped under the broad umbrella of "engagement" in the BPS codebook, I argue that it is reasonable to group them under the narrower umbrella of "affective engagement." This is because they focus on students' subjective experiences (opinions, attitudes), as opposed to their objective experiences (behaviors, activities). I refer to my measure of affective engagement as an affective engagement scale, and I interpret higher scores on the scale as indicative of higher levels of affective engagement.

In terms of validity, the fact that the underlying items for the affective engagement scale were adapted from NSSE should instill some confidence that the scale is capturing something meaningful about students' perceptions of their first-year college experience (National Survey of Student Engagement, n.d.). That said, it is worth noting that the distribution of the scale is left-skewed; few respondents have low scores, and many respondents have high scores. Thus, the scale may not be able to detect meaningful differences between people with relatively high levels of affective engagement. In terms of reliability, the scale meets conventional standards for statistical reliability ($\alpha = 0.84$).

I measure behavioral engagement by taking the sum of students' responses to a series of yes/no survey items regarding their use of campus services during the first year of college, including the following: academic advising, academic support, and career services.[57] For the purposes of this study, I interpret higher values on this scale as representing a higher level of

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[57] The survey also asked students about their use of financial aid and health services, but I opted to focus on the types of campus services that are more directly linked to students' academic pursuits. I include career services in my measure of behavioral engagement because career services offices can help students decide which major to pursue. They can also help to connect students, even first-year students, with internships. In supplementary analyses, I find similar results when I include all five yes/no variables.

behavioral engagement. Admittedly, this is a limited measure of behavioral engagement, as it does not capture things like the number of hours students spent studying, the frequency with which they met with professors, or the frequency with which they completed their academic assignments. Unfortunately, none of these were measured by BPS:12/17. I discuss this limitation in more detail in the Discussion and Conclusion section.

For ease of interpretability, I standardize the affective and behavioral engagement scales to have a mean of 0 and a standard deviation of 1.

College Selectivity. College selectivity is one of the key independent variables for this study. I use a simple, continuous measure of college selectivity, which is based on the median SAT score of admitted students.[58,59,60] I interpret colleges with higher median SAT scores as more selective, and vice versa. For ease of interpretability, I divide colleges' median SAT scores by 100. In addition, in my regression analyses, I center this variable at its mean, which is 11.18.

Race/ethnicity and Socioeconomic Status. Race/ethnicity and socioeconomic status are the other key independent variables for this study. I use the RACE variable from BPS:12/17 to group students into the following five racial/ethnic groups: White, Black, Hispanic, Asian, and

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[58] If a college reports ACT scores instead of SAT scores, I convert them to their SAT equivalents using a standard concordance table (Dorans, 1999). If a college reports ACT and SAT scores, I use whichever test type was more common for that college's applicant pool.

[59] Most four-year colleges report SAT data to IPEDS every year, but some colleges are missing data for some years. I address this missing data issue by using test score data from 2011, 2012, and 2013. If a college reported test score data for all three years, I take the average across all three years. If a college reported test score data for only two of the years, I take the average across those two years. Finally, if a college reported test score data for only one of the years, I use that year's data.

[60] I use a test-score based measure of selectivity because this is the most commonly used continuous measure of selectivity in the higher education literature (see, for example, Bowen et al., 2009; Dale & Krueger, 2002; Shamsuddin, 2016; Smith, 2013). As noted by Shamsuddin (2016, p. 800), "other measures of selectivity are more vulnerable to gaming by universities. For example, admissions offices may encourage applications from under-qualified students to lower the university acceptance rate, which is a commonly used factor in rankings by U.S. News and World Report and others."

Other. The Other category includes students who identify as Native American, Pacific Islander, or more than one race. I group these students together because, on their own, their sample sizes are too small to yield meaningful results. This is one of the limitations of working with nationally representative survey data; it is difficult to use these data to analyze subgroup-specific patterns for subgroups with small populations.

I measure socioeconomic status in terms of parental education and household income, as indicated by the PAREDUC and PELL12 variables in BPS:12/17. If a student reported that neither of their parents or guardians had a bachelor's degree or higher, I classify them as being a first-generation college student. If a student received a Pell Grant during their first year of college, I classify them as coming from a low-income background.[61] Using this information, I group students into the following four first-generation, low-income (FGLI) categories: (1) not first-generation, not low-income; (2) low-income only; (3) first-generation only; and (4) first-generation, low-income.

I acknowledge that the racial/ethnic and socioeconomic status categories that I use in this study are broad, and that they will not reflect the significant heterogeneity that exists within each of these subgroups (Castillo & Gilborn, 2022; Jack, 2019). That said, analyzing variation across these broad categories can shed light on important, high-level trends, and can be used as a starting point for future, finer-grained studies.

Covariates. To minimize bias and maximize the precision of my estimates, I use the following control variables in my regression models: size of first college (0-2,500 students,

[61] I use Pell Grant status as a proxy for income because it is based on students' Expected Family Contribution (EFC). Though it is not without flaws, EFC is a more nuanced measure of financial need than income alone, as it considers things like assets and family size, in addition to income.

2,501-5,000 students, 5,001-10,000 students, 10,001-20,000 students, and more than 20,000 students), control[62] of first college (public versus private), gender (female versus male), and pre-college academic qualifications (as indicated by students' SAT/ACT score and high school GPA). I selected these variables after reviewing the empirical and theorical literature on student engagement. This review helped me to identify factors that could lead me to misestimate the association between college selectivity and student engagement. For example, if I observe that students at more selective colleges tend to have higher levels of engagement, this could be because more selective colleges are doing a better job of promoting high levels of engagement. Alternatively, it could be because the students at more selective colleges have higher levels of pre-college academic qualifications, or because more selective colleges tend to have smaller student bodies. If this is the case, then failing to control for these variables in my regression models could lead me to overestimate the association between selectivity and engagement. That said, including control variables, while beneficial, does not allow me to rule out the possibility that there are other important differences between students at more and less selective colleges. I discuss this limitation in more detail in the Discussion and Conclusion section of this paper.

Weighting Variables. All my analyses use the appropriate weighting variables to account for the complex design of the BPS survey. Because my analyses only include variables from the 2011-12 survey wave, I use the cross-sectional balanced repeated replication (BRR) survey weights from BPS:12/17 (WTA000-WTA200). These weights restrict my analysis to respondents who participated in 2011-12 survey wave, while also adjusting my estimates so they

[62] In the higher education context, "control" is a term that refers to whether a college is publicly or privately operated.

are nationally representative. Recall that my analytic sample is restricted to four-year college students whose colleges reported valid SAT/ACT data to IPEDS in 2011, 2012, or 2013. This means that, when the appropriate weights are applied, my findings can be interpreted as representative of U.S. college students who meet these sampling criteria.

Analytic Strategy

In the first part of my analysis, I describe the characteristics of my sample and I examine the bivariate associations between college selectivity and my outcome variables of interest. Further, I describe how these bivariate associations vary across students from different racial/ethnic and socioeconomic backgrounds.

Next, I estimate a series of multivariate regression models. These regression models allow me to control for potential confounding and explanatory factors, thereby improving my ability to isolate the patterns I am seeking to describe. For each outcome variable, I estimate five regression models. The first model, “Baseline (Race),” examines the association between selectivity and the outcome variable, controlling for race/ethnicity and college-level confounders. The second model, “Baseline (FGLI),” examines the association between selectivity and the outcome variable, controlling for FGLI status and college-level confounders. The third model, “Full,” controls for race/ethnicity, FGLI status, college-level confounders, as well as students’ gender and pre-college academic qualifications. The fourth model, “Interaction (Race),” adds an interaction between selectivity and race/ethnicity to examine whether the association between selectivity and the outcome variable varies across students from different racial/ethnic backgrounds. The fifth model, “Interaction (FGLI),” includes an interaction between selectivity and FGLI status to examine whether the association between selectivity and the outcome variable varies across students from different socioeconomic backgrounds.

In the main part of my analysis, I estimate ordinary least squares (OLS) regression models with BRR survey weights. These weights adjust for the complex sampling design of the BPS survey (i.e., the nested structure of the data). In supplementary analyses, I estimate a series of multilevel regression models. These models allow me to examine whether my main findings are robust to an alternative method for accounting for the nested structure of the BPS data.[63]

Results

Descriptive Statistics by Race/ethnicity

Table 3.1 presents descriptive statistics for the full analytic sample and by race/ethnicity.[64] As shown in Column 1, White respondents make up roughly 65 percent of the sample, with Black, Hispanic, and Asian respondents making up roughly 11, 12, and 7 percent of the sample, respectively. The racial/ethnic breakdown of the analytic sample differs to some extent from the breakdown of the BPS sample overall, due to racial/ethnic differences in college destinations. Specifically, White and Asian respondents are overrepresented at four-year colleges, compared to their Black and Hispanic counterparts.

Turning to the outcome variables of interest, White students rank the highest in terms of affective engagement. The average affective engagement score for this subgroup is roughly 0.2 standard deviations higher than the average scores for Hispanic, Black, and Asian students.

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[63] Ideally, when working with complex survey data, one should be able to estimate weighted multilevel regression models (Shen & Konstantopoulos, 2022). However, to do so, one needs access to student-level as well as school-level weights. BPS does not provide school-level weights, so I estimate unweighted multilevel regression models.
[64] Due to the small size of the “other” category, Table 3.1 does not have a column for this subgroup of students.

However, when it comes to behavioral engagement, Asian students have the highest scores, followed by Black, Hispanic, and White students.

There are also some notable racial/ethnic differences in terms of college selectivity. Asian respondents attend the most selective colleges, on average, followed by White, Hispanic, and Black respondents. Figure 3.1 provides another look at college enrollment patterns by race/ethnicity. This figure divides colleges into three equally sized groups: low selectivity (median SAT is below 1050), medium selectivity (median SAT is between 1050 and 1150), and high selectivity (median SAT is above 1150). As shown by Figure 1, the share of White and Asian students increases as college selectivity increases, while the share of Black and Hispanic students decreases. This finding is consistent with prior research, which has shown that Black and Hispanic students are significantly underrepresented at selective colleges (Carnevale, 2018; Nichols, 2020).

One of the goals of this study is to examine the association between college selectivity and first-year engagement, and to see whether this association varies by race/ethnicity. Figures 3.2 and 3.3 show the mean affective and behavioral engagement scores for each racial/ethnic group, by college selectivity. These are simple, unadjusted means, so it is important to note that they do not account for factors that may confound or explain the associations between selectivity, race, and engagement. Figure 3.2 shows that, for White students, there is a positive association between selectivity and affective engagement during the first year of college. The same pattern appears to apply to Hispanic students. On average, Hispanic students at high selectivity colleges rate their affective engagement nearly 0.3 standard deviations higher than Hispanic students at medium and low selectivity colleges. That said, the means for Hispanic students are not very precisely estimated (i.e., the 95 percent confidence intervals for these means are quite wide), possibly because Hispanic students make up a relatively small share of the overall sample (just under 12 percent). This may also help to explain the noisy estimates for Black and Asian students, who make up 11 and 7 percent of the overall sample, respectively. For these groups, there is no clear pattern when it comes to selectivity and affective engagement during the first year of college.

Turning to behavioral engagement, Figure 3.3 shows that, for Black students, behavioral engagement, as indicated by students' use of campus services during the first year of college, is higher at medium and high selectivity colleges than it is at low selectivity colleges. The pattern for White students is similar in terms of direction, but more modest in terms of slope. For Hispanic and Asian students, behavioral engagement appears to be the highest at highly selective colleges, and somewhat lower at medium and low selectivity colleges.

To summarize, White students, who significantly outnumber their non-White peers at four-year colleges, report higher levels of affective engagement but lower levels of behavioral engagement than their non-White peers. In addition, for White and Hispanic students, there appears to be a positive association between selectivity and affective engagement. Finally for most students, there appears to be positive association between selectivity and behavioral engagement. Multivariate regression analyses can shed light on whether these simple descriptive patterns are artifacts of, or robust to, potential confounding or explanatory factors at the student and college level.

Descriptive Statistics by FGLI Status

Table 3.2 presents descriptive statistics for the full analytic sample and by first-generation, low-income (FGLI) status.[65] Looking at the sample overall, non-FGLI respondents make up roughly 49 percent of the sample, with LI only, FG only, and FGLI respondents making up roughly 12, 17, and 22 percent of the sample, respectively. As was the case with race/ethnicity, the FGLI status composition of the analytic sample differs to some extent from the composition of the BPS sample overall, due to socioeconomic differences in college destinations. For example, students who are neither first generation, nor low income—students in the non-FGLI category—comprise 29 percent of the overall BPS sample, but 49 percent of the analytic sample.

Turning to the engagement outcomes at the top of Table 3.2, as was the case with racial/ethnic differences, between-subgroup differences in first-year engagement vary depending on the type of engagement that is being analyzed. Students in the non-FGLI category report the highest levels of affective engagement. Indeed, the average affective engagement score for these students is roughly 0.15 to 0.2 standard deviations higher than the average score for students in the other three categories. By contrast, there are only minimal differences across the categories when it comes to behavioral engagement.

As was the case with race/ethnicity, there are also some notable FGLI status differences in terms of college selectivity. As shown by Table 3.2, non-FGLI respondents attend the most selective colleges, on average, followed by LI only, FG only, and FGLI respondents. Figure 3.4

[65] Recall that, for this study, I sort students into four FGLI status categories: not first generation, not low income (non-FGLI); low income only (LI only); first generation only (FG only); and first generation, low income (FGLI).

provides another look at how college enrollment patterns vary by FGLI status. This figure shows that as college selectivity increases, the share of non-FGLI students increases, while the share of FGLI and FG only students decreases. The share of LI only students is roughly equal across the three selectivity categories.

One of the primary goals of this study is to examine the association between college selectivity and first-year engagement, and to see whether that association varies by FGLI status. Figures 3.5 and 3.6 show the mean affective and behavioral engagement scores for each FGLI status group, by college selectivity. These are simple, unadjusted means, so it is important to note that they do not account for factors that may confound or explain the associations between selectivity, FGLI status, and engagement. Figure 3.5 shows that, for FGLI, LI only, and non-FGLI students, there is a positive association between selectivity and affective engagement. The pattern is less pronounced for FG only students. For these students, the association between selectivity and affective engagement appears to be relatively flat.

Turning to behavioral engagement, Figure 3.6 shows a somewhat similar pattern. There are clear positive associations between selectivity and behavioral engagement for FGLI, LI only, and non-FGLI respondents. For FG only respondents, these associations appear to be relatively flat.

To summarize, as was the case when examining racial/ethnic differences in affective and behavioral engagement, students in the non-marginalized group—in this case, non-FGLI students—report higher levels of affective engagement during the first year of college. By contrast, there are fewer differences across FGLI status categories when it comes to behavioral engagement during the first year of college, as indicated by students' use of campus services.

Moreover, bivariate analyses suggest that, for non-FGLI, LI only, and FGLI students, there are positive associations between selectivity and both types of engagement. Multivariate regression analyses can shed light on the extent to which these patterns are artifacts of, or robust to, potential confounding and explanatory factors at the student and college level.

Multivariate Regression Results: College Selectivity and Affective Engagement

Table 3.3 summarizes the results from a series of OLS regression models that examine the association between college selectivity and affective engagement, as indicated by students' responses to the five "engagement" items from the base-year BPS survey. Models 1 and 2 are baseline models. They examine whether there is a significant association between college selectivity and affective engagement, after controlling for race/ethnicity (Model 1), FGLI status (Model 2), and college-level confounders (both models). Across both models, the association between selectivity and affective engagement is positive and statistically significant. For example, using the college selectivity coefficient from Model 1, we can say that a 1-unit increase in selectivity (i.e., 100-point increase in a college's median SAT score) is associated with a 0.09 standard deviation increase in affective engagement, after controlling for race/ethnicity and college-level confounders ($p<0.001$).

In addition, Model 1 shows that, compared to White students, students who identify as Black, Hispanic, and Asian have lower levels of affective engagement, after controlling for college-level factors. Similarly, from Model 2, we can see that, compared to their non-FGLI counterparts, students who identify as FGLI and FG only report lower levels of affective engagement. These results align with the patterns observed in the simple descriptive analyses.

Model 3 examines whether the results from Models 1 and 2 are robust to additional control variables. In addition to including all the variables from Models 1 and 2, Model 3 controls for gender and pre-college academic preparation. Here, we can see that, even after controlling for numerous student-level and college-level variables, there is still a positive and statistically significant association between selectivity and affective engagement during the first year of college (b=0.064, p<0.001).

Models 4 and 5 are interaction models. Model 4 examines whether the association between selectivity and affective engagement varies by race/ethnicity, and Model 5 examines whether this association varies by FGLI status. Looking at both models, seven out of eight of the interaction coefficients are small and statistically insignificant. The only statistically significant interaction coefficient is the Black-by-selectivity interaction in Model 4 (b=-0.089, p<0.05). This indicates that, for Black students, the association between selectivity and affective engagement during the first year of college is relatively flat, and it may even be slightly negative. Indeed, for these students, a 100-point increase in a college's median SAT score corresponds with a 0.007 SD decrease in affective engagement. For comparison, for White students, 100-point increase in a college's median SAT score corresponds with a 0.082 SD increase in affective engagement. Figure 3.7, a plot of regression-adjusted affective engagement scores by race/ethnicity and college selectivity, illustrates this pattern graphically. Figure 3.7 shows that, all else being equal, the predicted affective engagement score for Black students at colleges with a median SAT of 900 is -0.06, compared to -0.09 for Black students at colleges with a median SAT of 1300. This is a very modest decline, so I argue that the trendline is best described as "relatively flat," as opposed to "negative."

Multivariate Regression Results: College Selectivity and Behavioral Engagement

Table 3.4 summarizes the results from a series of OLS regression models that examine the association between college selectivity and behavioral engagement, as measured by students' use of campus services during the first year of college. Models 1 and 2 are baseline models. They examine whether there is a significant association between college selectivity and behavioral engagement, after controlling for race/ethnicity (Model 1), FGLI status (Model 2), and college-level confounders (both models). Across both models, the association between selectivity and behavioral engagement is positive and statistically significant. For example, using the college selectivity coefficient from Model 1, we can say that, after controlling for race/ethnicity and college-level confounders, a 100-point increase in a college's median SAT score corresponds with a 0.067 SD increase in behavioral engagement ($p<0.001$).

In addition, from Model 1, we can see that, compared to White students, students who identify as Black, Hispanic, or Asian have higher levels of behavioral engagement, after controlling for college-level factors. From Model 2, we can see that there are only minimal differences across the FGLI categories when it comes to behavioral engagement. These results align with what we observed in preliminary descriptive analyses.

Model 3 examines whether the associations from Models 1 and 2 are robust to additional control variables. In addition to including all the variables from Models 1 and 2, Model 3 controls for students' gender and pre-college academic qualifications. The results from Model 3 indicate that, even after controlling for numerous student- and college-level factors, there is still a positive and statistically significant association between college selectivity and behavioral engagement during the first year of college (b=0.066, $p<0.001$).

Models 4 and 5 are interaction models. Model 4 examines whether the association between selectivity and behavioral engagement varies by race/ethnicity, and Model 5 examines whether this association varies by FGLI status. Across both models, all eight interaction coefficients are small and statistically insignificant. This indicates that the association between selectivity and behavioral engagement does not vary, to a statistically significant degree, across students from different racial/ethnic and socioeconomic backgrounds.

Robustness Checks and Exploratory Analyses

Multilevel Models. To test the robustness of my findings, I estimated a series of multilevel regression models. Similar to my main models, these multilevel models account for the nested structure of the BPS data. The main difference is that my main models do this by using BRR weights, while the multilevel models do it by explicitly modeling within-college and between-college variation. Results from these models, which are shown in Tables A3.1 and A3.2, are consistent with the results from my main OLS models.[66]

Binary Outcome Variables. As an additional robustness check, I estimated a series of linear probability models—OLS regression models with a binary, as opposed to a continuous, measure of affective engagement. In these models, students with above-average engagement scores were assigned a value of 1 (0 otherwise). Results from these models are consistent with the main OLS models and are presented in Tables A3.3 and A3.4.

Item-by-item Analysis. I also estimated a series of OLS regression models that examined the association between college selectivity and each of my five indicators of affective

[66] In results not shown, these models also confirm NSSE's claim that most of the variation in student engagement occurs within colleges, as opposed to between them (National Survey of Student Engagement, 2008).

engagement, as well as the association between college selectivity and each of my three indicators of behavioral engagement. Results from the single-item affective engagement models, presented in Tables A3.5-A3.9, suggest that the positive association between selectivity and affective engagement is being driven by peer interactions, social satisfaction, and belonging, as opposed to the faculty interactions and academic satisfaction. Results from the single-item behavioral engagement models, presented in Tables A3.10-A3.12, suggest that the positive association between selectivity and behavioral engagement is being driven by academic support and career services, as opposed to academic advising. These item-by-item results can be used to inform future research on the association between selectivity and engagement (i.e., research that seeks to identify *why* engagement varies by selectivity).

Exploratory Analyses. To investigate why the association between college selectivity and affective engagement is positive for most students, but flat for Black students, I estimated a set of exploratory regression models. In one set of models, I replaced the college selectivity variable with a "Percent Black" variable. In another set of models, I replaced the college selectivity variable with a "Percent White" variable. These variables indicate the percent of Black-identifying and White-identifying students at each respondent's college, according to IPEDS. Results from the first set of exploratory models, presented in Table A3.13, show that, for Black students, there is small, positive association between Percent Black and affective engagement ($b=0.007$, $p<0.10$). Results from the second set of exploratory models, presented in Table A3.14, show that, for Black students, there is a small, negative association between Percent White and affective engagement ($b=-0.008$, $p<0.001$). Both sets of results lend some support to the social isolation hypothesis, or the idea that, when students attend colleges where their background is underrepresented, they may find it more difficult to feel a strong connection to their college. More research is needed to understand whether these associations are causal, or whether they can be attributed to other factors.

Discussion and Conclusion

Up to this point, most of the research on the association between college selectivity and postsecondary outcomes has focused on persistence, graduation, and post-college employment and earnings. This study expands the scope of this research by focusing on student engagement. Using data from BPS:12/17, I find that, for most students, there is a positive association between college selectivity and affective engagement, as indicated by students' responses to a series of survey items about the positivity of their first-year experience. I also find that there is a positive association between college selectivity and behavioral engagement, as indicated by students' use of academic advising, academic support, and career services during the first year of college. These findings offer support for the resource hypothesis, or the idea that, when students attend more selective colleges (i.e., colleges with more financial resources), they will tend to experience higher levels of engagement. At the same time, I find that, for Black students, the association between selectivity and affective engagement is relatively flat, and that it may even be slightly negative. This offers some support for the social isolation hypothesis, or the idea that, when a student attends a college where their background is underrepresented, they may struggle to feel a strong social or emotional connection to their college.

By and large, findings from this study are consistent with much of the prior research on college selectivity, which has found that students who attend more selective colleges tend to experience more positive outcomes (Bound et al., 2010; Bowen et al., 2009; Hoxby & Avery, 2013; Shamsuddin, 2016). That said, findings from this study are *not* consistent with the existing research on college selectivity and student engagement, which has found that selectivity is not a significant predictor of student engagement (National Survey of Student Engagement, 2014). This may be because the 2014 NSSE study and the present study use different measures of student engagement. The differences between the two studies may also be attributable to the fact that the data from the 2014 NSSE study come from the NSSE survey, which is not a nationally representative survey and, as such, may not reflect overall trends in U.S. higher education.

My finding that the association between selectivity and affective engagement is positive for most students, but relatively flat for Black students, echoes some of the existing research on the day-to-day experiences of students from historically marginalized backgrounds at selective colleges (Armstrong & Hamilton, 2013; Jack, 2019). This research has found that selective colleges have significant room for improvement when it comes to supporting students from low-income, first-generation, and minoritized backgrounds. My study contributes to literature by showing that selective colleges may have an *especially* long way to go when it comes to fostering campus environments that are supportive and welcoming for Black students (i.e., combatting anti-Black racism, both inside and outside the classroom).

Interestingly, even though the association between selectivity and affective engagement is relatively flat for Black students, the association between selectivity and behavioral engagement is quite positive. One way to interpret this finding is that Black students at selective colleges do not appear to be withdrawing or disengaging from schooling-related activities, despite having less positive first-year experiences than their same-college peers. This aligns with the literature on racial discrimination, which has found that some people cope with adversity and discrimination by exhibiting high levels of resilience and self-regulation (E. Chen et al., 2015; E. Chen & Miller, 2012; Gaydosh et al., 2018; Geronimus et al., 2006). This can facilitate success and upward mobility, but it can also have a negative impact on mental and physical health. Thus, although I do not find sizable engagement-related downsides for Black students at selective colleges, future research should examine whether there are health-related downsides.

Drawing on Jack (2019), an alternative explanation for my finding regarding Black students and affective engagement is that, even after controlling for socioeconomic status, Black students' experiences at selective colleges may vary depending on their pre-college experiences (e.g., whether they attended an elite preparatory high school). According to Jack, low-income students who had prior exposure to elite schooling environments (the "privileged poor") had much smoother college transitions than low-income students with no prior exposure to elite schooling environments (the "doubly disadvantaged"). It is possible that, had I been able to classify students in this way, I would have seen a positive association between selectivity and affective engagement for Black students in the "privileged poor" group, and a negative association for Black students in the "doubly disadvantaged" group. Data limitations prevent me from examining this hypothesis directly, but it could be a fruitful avenue for future research.

Broadly speaking, more research is needed to understand why students at more selective colleges tend to have higher levels of engagement. One possibility has to do with financial resources; resource-rich institutions may have an advantage when it comes to promoting student engagement. Alternatively, it may be that some other aspect of selective colleges, unrelated to financial resources, is causing students to have higher levels of engagement. It is also possible that the relationship between selectivity and engagement is not causal. Instead, it may be an artifact of unobserved differences between students at more and less selective colleges. For example, perhaps students at more selective colleges have higher levels of engagement because they have higher levels of academic motivation. In this study, due to data limitations, I am unable to rule out these possibilities. Future research, using experimental or quasi-experimental methods, should examine whether the link between selectivity and engagement is robust to these kinds of alternative explanations.

Future research should also examine the link between college selectivity, student engagement, and other indicators of student wellbeing, including students' mental and physical health. Given the existing research on the link between day-to-day experiences and mental and physical health outcomes (Adam et al., 2015; Destin, 2019; Gaydosh et al., 2018; Sapolsky, 2004), it seems plausible that higher levels of engagement could be related to higher levels of mental and physical health. However, due to data limitations (i.e., the fact that BPS:12/17 does not include detailed measures of students' mental or physical health), I am unable to examine this question in this paper.

As I note above, this descriptive study is limited in that it cannot be used to explain the association between selectivity and engagement, nor can it shed light on the associations between selectivity, engagement, and mental and physical health. Another limitation to bear in mind is that the affective engagement scale that I use for this study may suffer from ceiling effects. This means it may not be able to capture important differences between people with relatively high levels of affective engagement. In addition, my measure of behavioral engagement focuses on students' use of campus services. It does not capture other important aspects of behavioral engagement, such as going to class, completing assignments, or discussing class material with professors or peers. These things may or may not be correlated with students' use of campus services. Thus, it is possible that, were I to use a different measure, I may come to a different conclusion about the association between selectivity and behavioral engagement. To address this limitation, scholars should advocate for the inclusion of more detailed measures of student engagement on future nationally representative surveys of college students.[67]

Another notable limitation is that present study focuses exclusively on the first year of college. Although many scholars have argued that the first year of college sets the tone for students' college experience, it is possible that the engagement-related patterns I observe during the first year of college will not carry over to subsequent years. For example, for some students, the association between selectivity and engagement may fade over time. Future research should investigate this, while taking care to account for fact that there may be important differences between students who remain at their original college, students who transfer to another institution, and students who drop out of college altogether.

Despite its limitations, this study has important implications for future, policy-relevant research on the college selectivity and, more broadly, on inequality in higher education. As I have already noted, future research should seek to understand the mechanisms that are driving the association between selectivity and engagement. If financial resources are an important mediating factor, this would offer support for the argument that policymakers should do more to address funding disparities between more and less selective colleges. This could lead to more equitable postsecondary outcomes, not just in terms of engagement, but also in terms of persistence, graduation, and employment. If, on the other hand, the relationship between

[67] Scholars should also advocate for more detailed measures of students' mental and physical health.

selectivity and engagement is not mediated by financial resources, this would offer support for the idea that, to improve student engagement, colleges should examine, assess, and adjust their internal structures and practices (National Survey of Student Engagement, 2008, 2014).

Although more research is needed, this study contributes to ongoing debates about college choice, including debates about the extent to which prospective college students should prioritize things like selectivity and prestige during the college search process. Overall, I argue that this study offers additional support for the argument that, in general, attending a more selective college will increase one's likelihood of experiencing positive postsecondary outcomes. That said, there is a need for more research on the association between college selectivity and other types of outcomes, including mental and physical health outcomes.

Several studies have highlighted the fact that, for students from low-income, first-generation, and minoritized backgrounds, selective colleges can be isolating and difficult to navigate. Given this, some have wondered whether *less* selective colleges may offer more welcoming and engaging environments for students from these backgrounds. This study uses nationally representative survey data to examine whether this might be the case. I find that, contrary to this hypothesis, most students report higher levels of engagement at more selective, as opposed to less selective, colleges. This pattern is robust to several possible confounding factors, including college type, college size, and students' pre-college academic qualifications. Although more research is needed, this study lends some additional support to the argument that selective colleges have important advantages over their less selective counterparts. At the same time, this study adds nuance to this argument by highlighting how, when it comes to affective engagement, some students appear to be benefiting from the selective college environment more than others.

Conclusion

Improving bachelor's degree completion rates and narrowing BA attainment gaps is crucial to ensuring that the U.S. higher education system lives up to its promise of being an engine for social and economic mobility (Kelly & Schneider, 2012; Lederman, 2010; McNair et al., 2016; Mehaffy, 2018). In this dissertation, I contribute to the literature on BA completion by exploring the choices and tradeoffs that students face as they make their way towards a bachelor's degree. Drawing on several nationally representative data sources and using an array of quantitative methods, I find evidence that college choice continues to be an important predictor of degree completion (Study 1); that cost may help to explain why some students prioritize college proximity over academic fit (Study 2); and that college choice, in addition to being an important predictor of degree completion, is also an important predictor of student engagement (Study 3).

Findings from Study 1 and Study 3 are consistent with prior research on college choice and postsecondary outcomes, which has found that, generally speaking, students experience better outcomes when they attend more selective colleges (Bowen et al., 2009; Dillon & Smith, 2020; Ovink et al., 2018; Shamsuddin, 2016). However, as I have noted throughout, the link between college selectivity and postsecondary outcomes is complicated. This is because more selective colleges differ from their less selective counterparts, not just in terms of their admissions criteria and resources, but also in terms of their demographics. As I discuss in Study 3, for students from low-income, first-generation, and minoritized backgrounds, attending a more selective college does not simply mean attending a college with more resources and prestige. In most cases, it also means attending a college with relatively few students from similar backgrounds. I theorize that this may dampen some of the positive effects of attending a selective college, and I find evidence that, for Black students, this may very well be the case. This highlights the continued importance of work to improve diversity, equity, and inclusion in higher education, especially at selective colleges.

Turning to Study 2, findings from this study are consistent with prior research on college proximity and college choice, which has found that college proximity can be an important determinant of college choice and, consequently, postsecondary outcomes (Dillon & Smith, 2017; Ovink et al., 2018). Specifically, Study 2 offers some preliminary support for the "cost hypothesis," or the idea that distance-related costs may discourage students from attending far-away colleges. This is evidenced by my finding that, when students have no choice but to attend colleges that are relatively far away, they appear to face higher college costs. Still, this finding is descriptive and statistically noisy, and it relies on an incomplete indicator of college costs, so it should be interpreted with caution.

This dissertation makes several valuable contributions to the existing literature, but it also has some important limitations. Two are worth emphasizing here. First, it is important to note that all three studies are descriptive (i.e., correlational) in nature. While I have done my best to account for potential alternative explanations and confounding factors, my research designs ultimately do not allow for causal inferences. A second limitation has to do with the fact this dissertation relies on secondary data sources (i.e., data that were collected by other researchers). This means that, in some cases, I have had to make compromises when it comes to defining and operationalizing my variables. For example, in Study 1, it would have been ideal to have more data on students' pre-college academic qualifications. In Study 2, it would have been ideal to have a more detailed measure of college costs. Finally, in Study 3, it would have been ideal to have a more detailed measure of behavioral engagement. In the end, I have done my best to be a resourceful and diligent user of secondary data, while also taking care to identify and emphasize important opportunities for future data collection efforts.

Despite these limitations, this dissertation has important implications for future research on college choice and postsecondary outcomes. Specifically, building on Study 1, future research should seek to understand *why* college choice continues to be such an important predictor of BA completion. Building on Study 2, future research should continue to investigate whether it is more costly to attend a far-away college, and whether this plays a role in students' decisions to attend nearby colleges. Finally, building on Study 3, future research should continue to embrace a holistic approach to measuring postsecondary outcomes; in addition to focusing on things like BA completion and labor market outcomes, scholars should also focus on things like engagement, psychological wellbeing, and physical health.

This dissertation also has implications for policymakers, practitioners, and prospective college students. Many of the findings from this dissertation offer support for the argument that, in many cases and for many reasons, college choice matters. As I note in Study 1, one way to reduce the significance of college choice would be to reduce resource-related disparities between colleges. This is a worthwhile goal, but it is not going to be achieved overnight. In the meantime, it is important for prospective college students to know that there are important differences between colleges—differences that could affect their likelihood of completing a degree. Given this, I argue that policies and programs that help students navigate the college choice process continue to be worthwhile. Furthermore, I argue that these policies and programs should continue to be updated and expanded to reflect the latest research on college choice and postsecondary outcomes.

In sum, this dissertation addresses several policy-relevant gaps in the college choice literature. By examining the association between college choice and BA completion (Study 1), the association between college proximity and college costs (Study 2), and the association between college selectivity and student engagement (Study 3), this dissertation generates valuable insights about the choices and tradeoffs that students face as they make their way towards a bachelor's degree. These descriptive insights pave the way for future research on college choice, college affordability, and student engagement, as well as future efforts to promote more equitable postsecondary outcomes in the U.S. and beyond.

Tables and Figures

Study 1 Tables

Table 1.1: Descriptive Statistics by Cohort: Weighted Means and Proportions

	1995 Cohort	2003 Cohort	2011 Cohort
Match Status			
Undermatched	0.28	0.27	0.27
Matched	0.41	0.45	0.44
Overmatched	0.30	0.28	0.29
Academic Preparation Variables			
SAT/ACT	1000.93	1002.91	1012.76
	(202.01)	(211.41)	(188.29)
HS GPA			
A- to A	0.32	0.40	0.27
B to A-	0.34	0.35	0.39
B- to B	0.16	0.13	0.14
C to B-	0.14	0.10	0.16
C and below	0.04	0.02	0.04
Highest Math Class Taken in HS			
Algebra or Geometry	0.12	0.09	0.10
Algebra 2	0.26	0.26	0.25
Trigonometry	0.18	0.19	0.11
Pre-calculus	0.23	0.25	0.25
Calculus	0.22	0.21	0.30
Demographic Variables			
Most Educated Parent's Level of Education			
HS or Less / Don’t Know	0.31	0.25	0.28
Some College	0.19	0.26	0.26
BA	0.28	0.25	0.23
More than BA	0.22	0.24	0.22
Dependent	0.96	0.94	0.89
Woman	0.55	0.57	0.58
Underrepresented Racial/Ethnic Minority	0.20	0.26	0.36

	1995 Cohort	2003 Cohort	2011 Cohort
Age	18.45	18.57	18.77
	(1.04)	(1.01)	(1.52)
Selectivity of First College Attended			
Very Selective	0.16	0.12	0.12
Selective	0.17	0.15	0.16
Somewhat Selective	0.24	0.25	0.22
Nonselective	0.08	0.08	0.08
Two-year or Less	0.35	0.39	0.42
Outcome Variable			
6-Year BA Completion	0.49	0.49	0.48
N (Unweighted)	5,270	9,650	12,000
N (Weighted)	1,433,570	1,946,370	2,992,650

Notes. Standard deviations for continuous variables are shown in parentheses.

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table 1.2: Selected Cohort-specific Logistic Regression Results from Models Predicting BA Completion

	Panel 1: Main Analytic Sample			Panel 2: Sample Restricted to 4-year College Goers			Panel 3: Sample Restricted to Top Three Selectivity Categories		
	1995 Cohort	2003 Cohort	2011 Cohort	1995 Cohort	2003 Cohort	2011 Cohort	1995 Cohort	2003 Cohort	2011 Cohort
Match Status (Reference: Matched)									
Undermatched	0.615***	0.500***	0.414***	0.779*	0.786	0.540***	0.783	0.881	0.684*
	(0.0665)	(0.0473)	(0.0413)	(0.091)	(0.104)	(0.078)	(0.118)	(0.111)	(0.111)
Overmatched	2.250***	2.416***	3.416***	1.470**	1.267*	1.417*	1.580**	1.298*	1.454*
	(0.286)	(0.213)	(0.351)	(0.193)	(0.142)	(0.204)	(0.247)	(0.158)	(0.230)
N (Unweighted)	5,270	9,650	12,000	3,810	5,140	5,020	3,260	4,460	4,210
N (Weighted)	1,433,570	1,946,370	2,992,650	724,750	895,660	1,294,170	610,440	749,890	1,081,930

Notes. Exponentiated coefficients (odds ratios); standard errors in parentheses. All models control for high school academic preparation and demographic characteristics, but not college selectivity.

* p<0.05, ** p<0.01, *** p<0.001

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table 1.3: Six-year BA Completion Rates by Academic Match, Cohort, and Selectivity of First College Attended

	Undermatched				Matched				Overmatched			
	1995 Cohort	2003 Cohort	2011 Cohort	Δ from 1995 to 2011	1995 Cohort	2003 Cohort	2011 Cohort	Δ from 1995 to 2011	1995 Cohort	2003 Cohort	2011 Cohort	Δ from 1995 to 2011
Overall	0.52	0.51	0.46	-0.06	0.43	0.42	0.38	-0.05	0.54	0.6	0.64	+0.10
Very Selective	.	.	.	.	0.88	0.91	0.93	+0.05	0.79	0.81	0.84	+0.05
Selective	0.82	0.9	0.86	+0.04	0.77	0.82	0.87	+0.10	0.6	0.66	0.74	+0.14
Somewhat Selective	0.74	0.8	0.79	+0.05	0.57	0.67	0.68	+0.11	0.36	0.49	0.55	+0.19
Nonselective	0.61	0.64	0.52	-0.09	0.53	0.51	0.66	+0.13	0.35	0.32	0.36	+0.01
Two-year or Less	0.32	0.28	0.23	-0.09	0.13	0.13	0.10	-0.03	.	.	.	.

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table 1.4: Selected Cross-cohort Logistic Regression Results from Models Predicting BA Completion: 1995 Cohort vs. 2003 and 2011 Cohorts

	Panel 1: Main Analytic Sample			Panel 2: Sample Restricted to 4-year College Goers			Panel 3: Sample Restricted to Top Three Selectivity Categories		
	Under-matched	Matched	Over-matched	Under-matched	Matched	Over-matched	Under-matched	Matched	Over-matched
Cohort (Ref: 1995)									
2003 Cohort	0.980	1.115	1.111	1.252	1.246	1.045	1.370*	1.301*	1.067
	(0.146)	(0.162)	(0.0941)	(0.189)	(0.149)	(0.118)	(0.208)	(0.158)	(0.143)
2011 Cohort	0.965	1.215	1.594***	1.282	1.713***	1.503**	1.492*	1.714***	1.520**
	(0.142)	(0.179)	(0.138)	(0.180)	(0.223)	(0.187)	(0.240)	(0.228)	(0.237)
N (Unweighted)	6,660	11,730	8,530	3,670	5,950	4,360	2,850	5,760	3,320
N (Weighted)	1,741,890	2,792,970	1,837,730	800,920	1,217,340	896,630	597,830	1,171,520	672,300

Notes. Exponentiated coefficients (odds ratios); standard errors in parentheses. All models control for high school academic preparation, demographic characteristics, and college selectivity.

* p<0.05, ** p<0.01, *** p<0.001

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01) and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table 1.5: Results from Nonlinear Oaxaca-Blinder Regression Decompositions

	Panel 1: Main Analytic Sample			Panel 2: Sample Restricted to 4-year College Goers			Panel 3: Sample Restricted to Top Three Selectivity Categories		
	Under-matched	Matched	Over-matched	Under-matched	Matched	Over-matched	Under-matched	Matched	Over-matched
BA Completion Rate in 1995	0.519	0.430	0.539	0.729	0.733	0.707	0.770	0.741***	0.763***
BA Completion Rate in 2011	0.460	0.383	0.639	0.745	0.813	0.787	0.815	0.819***	0.828***
Difference Between 1995 and 2011	0.059	0.047	-0.100***	-0.016	-0.080***	-0.080***	-0.045	-0.078***	-0.065**
Explained Difference [a]	0.050**	0.074***	-0.005	0.017	0.010	-0.016	0.013	0.013	-0.015
Changes in academic variables	0.002	0.006	-0.017**	0.011	0.005	-0.014	0.016	0.007	-0.001
Changes in demographic variables	0.033***	0.035***	-0.002	0.008	0.001	-0.004	-0.004	0.001	-0.015
Changes in college selectivity	0.014	0.033**	0.009	-0.001	0.004	0.002	0.000	0.005	0.002
Unexplained Difference [b]	0.010	-0.027	-0.095***	-0.033	-0.090***	-0.064*	-0.058*	-0.091***	-0.050*

Notes. Due to rounding, values may not sum up exactly. Survey weights were used.

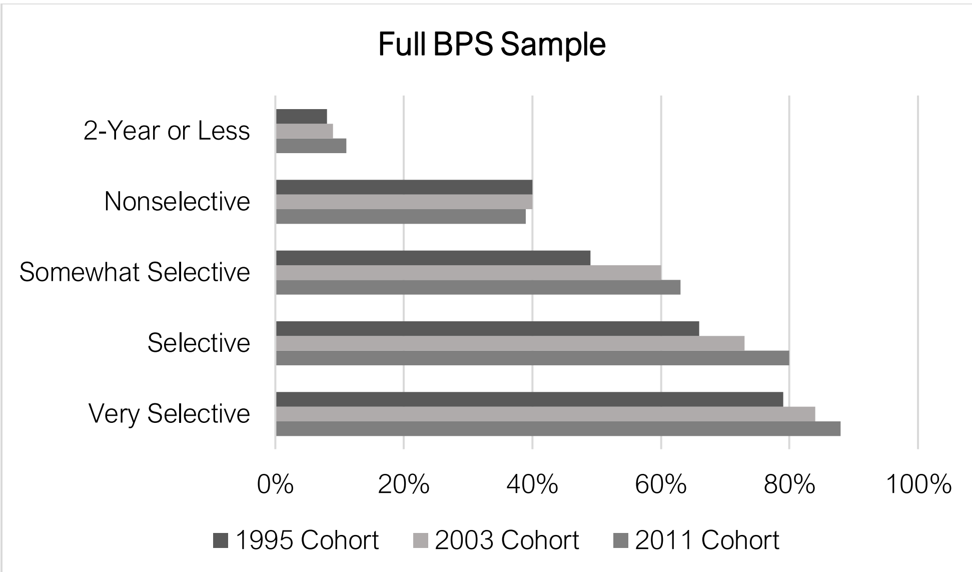
[a] Difference associated with changes in observed characteristics. [b] Difference associated with changes in coefficients or changes in unobserved characteristics.

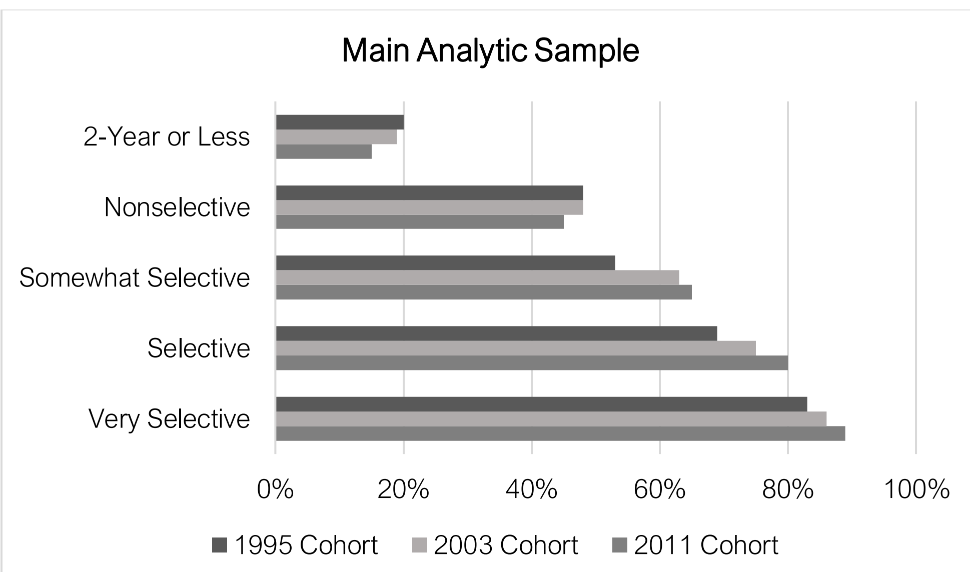
* p<0.05, ** p<0.01, *** p<0.001

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01) and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Study 1 Figures

Figure 1.1: Six-Year BA Completion Rates by Selectivity of First College Attended, Full BPS Sample vs. Main Analytic Sample





Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Study 2 Tables

Table 2.1: Descriptive Statistics by Geographic Access (County-level Measure)

	Full sample	Geog. access: High	Geog. access: 4-yr. only	Geog. access: 2-yr. only	Geog. access: Low
Took out a Stafford or Perkins loan, AY 1314	0.386	0.375	0.481	0.360	0.425
	(0.010)	(0.019)	(0.033)	(0.018)	(0.022)
Stafford & Perkins loans, AY 1314	2,101.494	2,056.772	2,586.663	1,948.376	2,325.591
	(55.886)	(108.447)	(202.959)	(110.344)	(142.635)
County-level access: High	0.405	1.000	0.000	0.000	0.000
	(0.023)	(.)	(.)	(.)	(.)
4-yr. only	0.063	0.000	1.000	0.000	0.000
	(0.010)	(.)	(.)	(.)	(.)
2-yr. only	0.349	0.000	0.000	1.000	0.000
	(0.024)	(.)	(.)	(.)	(.)
Low	0.183	0.000	0.000	0.000	1.000
	(0.015)	(.)	(.)	(.)	(.)
Distance traveled	125.612	134.403	131.780	121.827	111.216
	(4.483)	(8.519)	(24.110)	(7.771)	(8.790)
Distance traveled: Top-code flag	0.036	0.048	0.034	0.032	0.020
	(0.004)	(0.008)	(0.016)	(0.005)	(0.005)
Distance traveled is above the median	0.500	0.442	0.489	0.500	0.633
	(0.012)	(0.018)	(0.038)	(0.023)	(0.025)
HS GPA	3.167	3.109	3.267	3.192	3.211
	(0.017)	(0.032)	(0.067)	(0.030)	(0.037)
HS GPA: Imputation flag	0.035	0.042	0.012	0.043	0.011
	(0.008)	(0.015)	(0.009)	(0.013)	(0.007)
Race/ethnicity: White	0.548	0.423	0.733	0.585	0.690
	(0.013)	(0.027)	(0.037)	(0.024)	(0.026)
Asian	0.047	0.075	0.026	0.036	0.015
	(0.006)	(0.012)	(0.011)	(0.007)	(0.003)
Black	0.122	0.141	0.096	0.109	0.114
	(0.009)	(0.015)	(0.026)	(0.015)	(0.021)

	Full sample	Geog. access: High	Geog. access: 4-yr. only	Geog. access: 2-yr. only	Geog. access: Low
Hispanic	0.200 (0.011)	0.271 (0.022)	0.073 (0.023)	0.189 (0.024)	0.104 (0.017)
Other	0.083 (0.005)	0.090 (0.009)	0.071 (0.014)	0.081 (0.009)	0.076 (0.009)
Female	0.539 (0.009)	0.521 (0.017)	0.562 (0.027)	0.541 (0.017)	0.571 (0.016)
HS region: South	0.374 (0.008)	0.237 (0.024)	0.368 (0.083)	0.424 (0.033)	0.582 (0.040)
Northeast	0.199 (0.007)	0.257 (0.029)	0.213 (0.065)	0.201 (0.030)	0.061 (0.024)
Midwest	0.202 (0.009)	0.173 (0.019)	0.326 (0.076)	0.184 (0.024)	0.260 (0.031)
West	0.225 (0.009)	0.332 (0.030)	0.093 (0.055)	0.191 (0.038)	0.097 (0.029)
SES	0.128 (0.019)	0.119 (0.032)	0.222 (0.055)	0.150 (0.037)	0.075 (0.036)
One-parent household	0.234 (0.007)	0.228 (0.012)	0.225 (0.031)	0.233 (0.013)	0.256 (0.018)
1st college: 4-yr. public	0.439 (0.011)	0.396 (0.017)	0.612 (0.036)	0.436 (0.022)	0.477 (0.022)
4-yr. private	0.181 (0.008)	0.209 (0.013)	0.176 (0.034)	0.160 (0.014)	0.162 (0.017)
2-yr. public	0.347 (0.013)	0.354 (0.020)	0.189 (0.040)	0.377 (0.026)	0.330 (0.021)
2-yr. private	0.001 (0.000)	0.001 (0.001)	*	0.002 (0.001)	*
For-profit	0.032 (0.004)	0.040 (0.008)	0.023 (0.009)	0.025 (0.004)	0.030 (0.006)
HS locale: City	0.317 (0.013)	0.523 (0.034)	0.238 (0.071)	0.210 (0.036)	0.092 (0.031)
Suburb	0.306 (0.015)	0.305 (0.030)	0.226 (0.060)	0.409 (0.041)	0.139 (0.032)
Town	0.109 (0.011)	0.023 (0.010)	0.165 (0.060)	0.134 (0.026)	0.236 (0.038)

	Full sample	Geog. access: High	Geog. access: 4-yr. only	Geog. access: 2-yr. only	Geog. access: Low
Rural	0.267	0.148	0.371	0.248	0.534
	(0.013)	(0.025)	(0.080)	(0.030)	(0.044)
N(Unweighted)	9,000	3,540	690	3,040	1,740
N(Weighted)	2,178,330	882,160	137,690	760,740	397,740

Note. All statistics were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

* Not reported to protect subgroups with fewer than 3 respondents.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table 2.2: OLS Regression Results from Models Estimating the Association between Geographic Access and Logged Distance Traveled

	(1) Geog. access only	(2) + controls	(3) + college type
County-level access (Ref: High)			
4-yr. only	0.120	0.009	-0.088
	(0.137)	(0.137)	(0.139)
2-yr. only	0.071	0.034	0.144
	(0.116)	(0.111)	(0.102)
Low	0.551***	0.534***	0.574***
	(0.095)	(0.093)	(0.090)
N(Unweighted)	9,000	9,000	9,000
N(Weighted)	2,178,330	2,178,330	2,178,330
R-squared	0.01	0.13	0.28

Notes. Models 2 and 3 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), SES, and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Model 3 also controls for the sector and control of respondents' first college (ref: 4-yr. public). All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

+ $p<0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table 2.3: LPM and OLS Regression Results from Models Estimating the Association between Distance Traveled and Student Debt

	Panel A: Linear Probability Models			Panel B: OLS Models		
	(1) Dist. traveled only	(2) + controls	(3) + college type	(4) Dist. traveled only	(5) + controls	(6) + college type
Distance traveled quintile (Ref: 1st quintile)						
2nd quintile	0.020	0.040	0.009	0.197	0.374	0.106
	(0.037)	(0.033)	(0.031)	(0.311)	(0.283)	(0.267)
3rd quintile	0.181***	0.175***	0.082**	1.594***	1.540***	0.735***
	(0.028)	(0.027)	(0.026)	(0.233)	(0.230)	(0.214)
4th quintile	0.313***	0.311***	0.172***	2.741***	2.721***	1.516***
	(0.027)	(0.027)	(0.026)	(0.228)	(0.233)	(0.221)
5th (highest) quintile	0.280***	0.295***	0.124***	2.446***	2.572***	1.086***
	(0.026)	(0.027)	(0.027)	(0.218)	(0.226)	(0.225)
N(Unweighted)	9,000	9,000	9,000	9,000	9,000	9,000
N(Weighted)	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330
R-squared	0.07	0.14	0.22	0.07	0.14	0.23

Notes. Models 2, 3, 5, and 6 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), SES, and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Models 3 and 6 also control for the sector and control of respondents' first college (ref: 4-yr. public). All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table 2.4: LPM and OLS Regression Results from Models Estimating the Association between Geographic Access and Student Debt

	Panel A: Linear Probability Models				Panel B: OLS Models			
	(1) Geog. access only	(2) + controls	(3) + college type	(4) + dist. traveled	(5) Geog. access only	(6) + controls	(7) + college type	(8) + dist. traveled
County-level access (Ref: High)								
4-yr. only	0.105** (0.036)	0.056+ (0.031)	0.031 (0.027)	0.033 (0.027)	0.890** (0.312)	0.472+ (0.265)	0.255 (0.232)	0.272 (0.231)
2-yr. only	-0.015 (0.029)	-0.023 (0.022)	0.006 (0.020)	-0.005 (0.020)	-0.135 (0.251)	-0.202 (0.185)	0.049 (0.172)	-0.047 (0.167)
Low	0.050+ (0.030)	0.038 (0.027)	0.048+ (0.025)	0.015 (0.026)	0.423 (0.258)	0.323 (0.229)	0.414+ (0.216)	0.127 (0.224)
N(Unweighted)	9,000	9,000	9,000	9,000	9,000	9,000	9,000	9,000
N(Weighted)	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330
R-squared	0.00	0.08	0.20	0.22	0.00	0.08	0.21	0.23

Notes. Models 2-4 and 6-8 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), SES, and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Models 3-4 and 7-8 also control for the sector and control of respondents' first college (ref: 4-yr. public). Finally, Models 4 and 8 control for the distance between students' high schools and colleges. The models use the quintile version of distance traveled (ref: 1st (lowest) quintile). All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Study 2 Figures

Figure 2.1: Conceptual Model Depicting Average College Costs for People with Varying Levels of Geographic Access to Higher Education

		Distance to 4-yr. college	
		Near	Far
Distance to 2-yr. college	Near	Roughly equal chance of attending a 2-yr. or 4-yr. college • Tuition: May be high or low Possible to attend a nearby college • Living expenses: Relatively low	More likely to attend a 2-yr. college • Tuition: Relatively low Possible to attend a nearby college • Living expenses: Relatively low
	Far	More likely to attend a 4-yr. college • Tuition: Relatively high Possible to attend a nearby college • Living expenses: Relatively low	Roughly equal chance of attending a 2-yr. or 4-yr. college • Tuition: May be high or low **Not** possible to attend a nearby college • Living expenses: Relatively high

Figure 2.2: Geographic Access Categories

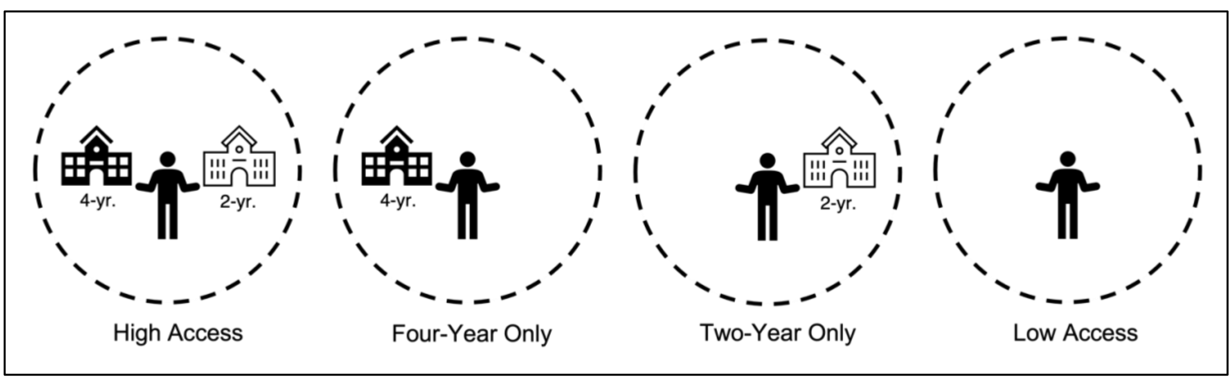
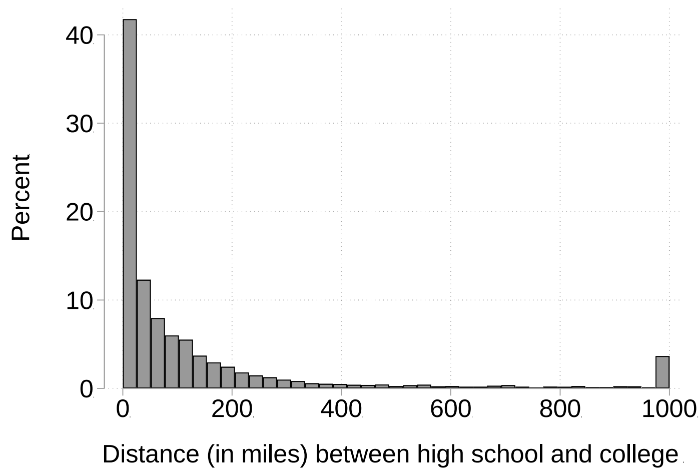
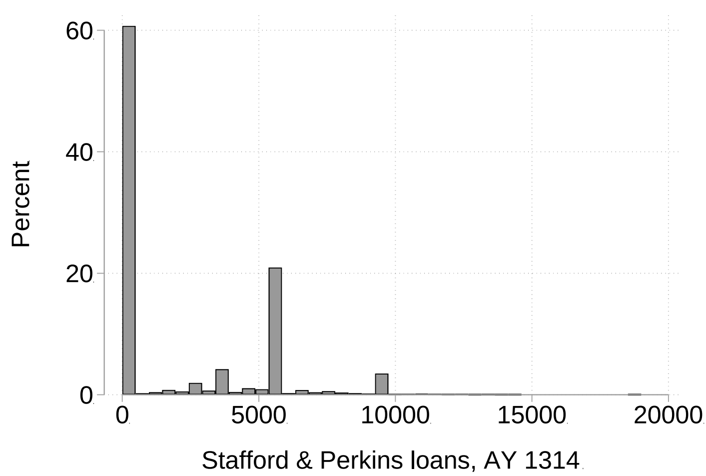


Figure 2.3: Distribution of the Distance Traveled Variable



Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Figure 2.4: Distribution of the Student Debt Variable



Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Study 3 Tables

Table 3.1: Descriptive Statistics by Race/ethnicity

	Full sample	White	Black	Hispanic	Asian
Affective engagement (z-score)	-0.007	0.068	-0.149	-0.191	-0.115
	(0.019)	(0.022)	(0.050)	(0.052)	(0.067)
Behavioral engagement (z-score)	-0.005	-0.035	0.041	0.026	0.129
	(0.018)	(0.020)	(0.064)	(0.047)	(0.065)
Median SAT of 1st college, divided by 100	11.182	11.337	10.193	10.926	11.723
	(0.035)	(0.036)	(0.089)	(0.074)	(0.104)
Control of first college: Public	0.635	0.623	0.670	0.679	0.618
	(0.008)	(0.011)	(0.032)	(0.023)	(0.033)
Private	0.365	0.377	0.330	0.321	0.382
	(0.008)	(0.011)	(0.032)	(0.023)	(0.033)
College enrollment: 0-2,500	0.120	0.132	0.126	0.077	0.056
	(0.007)	(0.009)	(0.022)	(0.010)	(0.015)
2,501-5,000	0.117	0.121	0.176	0.089	0.056
	(0.009)	(0.009)	(0.038)	(0.015)	(0.011)
5,001-10,000	0.177	0.171	0.259	0.167	0.121
	(0.009)	(0.011)	(0.034)	(0.021)	(0.020)
10,001-20,000	0.241	0.234	0.229	0.277	0.264
	(0.010)	(0.012)	(0.026)	(0.024)	(0.029)
More than 20,000	0.344	0.341	0.210	0.390	0.504
	(0.011)	(0.014)	(0.026)	(0.025)	(0.036)
Racial/ethnic identity: White	0.647				
	(0.010)				
Black	0.111				
	(0.007)				
Hispanic	0.119				
	(0.005)				
Asian	0.073				
	(0.005)				
Other	0.049				
	(0.004)				
FGLI status: Not first-gen, not low-income	0.487	0.580	0.217	0.281	0.442
	(0.007)	(0.010)	(0.023)	(0.021)	(0.030)

	Full sample	White	Black	Hispanic	Asian
Low-income only	0.121	0.106	0.155	0.146	0.135
	(0.005)	(0.006)	(0.019)	(0.015)	(0.022)
First-gen only	0.169	0.183	0.137	0.159	0.122
	(0.006)	(0.008)	(0.018)	(0.019)	(0.023)
First-gen, low-income	0.223	0.130	0.491	0.414	0.302
	(0.007)	(0.008)	(0.031)	(0.022)	(0.033)
Gender: Female	0.576	0.571	0.588	0.611	0.556
	(0.009)	(0.011)	(0.027)	(0.026)	(0.028)
Student SAT/100	10.965	11.276	9.654	10.293	11.329
	(0.039)	(0.042)	(0.133)	(0.100)	(0.142)
Student SAT: Imputation flag	0.002	0.001	*	*	*
	(0.001)	(0.001)			
HS GPA: C or below	0.002	0.001	0.008	0.008	*
	(0.001)	(0.000)	(0.003)	(0.004)	
C to B-	0.084	0.054	0.252	0.088	0.067
	(0.005)	(0.004)	(0.026)	(0.012)	(0.015)
B- to B	0.124	0.109	0.216	0.155	0.069
	(0.006)	(0.007)	(0.023)	(0.016)	(0.013)
B to A-	0.419	0.412	0.376	0.468	0.429
	(0.007)	(0.010)	(0.025)	(0.020)	(0.028)
A- to A	0.370	0.424	0.148	0.281	0.435
	(0.008)	(0.010)	(0.022)	(0.019)	(0.030)
N(Unweighted)	5,150	3,330	540	660	370
N(Weighted)	1,226,660	794,150	136,690	146,390	89,700

Note. All statistics were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

* Not reported to protect subgroups with fewer than 3 respondents.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table 3.2: Descriptive Statistics by FGLI Status

	Full sample	Non-FGLI	LI only	FG only	FGLI
Affective engagement (z-score)	-0.007	0.085	-0.055	-0.078	-0.130
	(0.019)	(0.020)	(0.049)	(0.047)	(0.040)
Behavioral engagement (z-score)	-0.005	0.002	0.073	-0.061	-0.020
	(0.018)	(0.026)	(0.049)	(0.040)	(0.042)
Median SAT of 1st college, divided by 100	11.182	11.620	11.141	10.896	10.465
	(0.035)	(0.046)	(0.066)	(0.046)	(0.053)
Control of first college: Public	0.635	0.598	0.593	0.699	0.690
	(0.008)	(0.012)	(0.022)	(0.016)	(0.017)
Private	0.365	0.402	0.407	0.301	0.310
	(0.008)	(0.012)	(0.022)	(0.016)	(0.017)
College enrollment: 0-2,500	0.120	0.111	0.127	0.111	0.143
	(0.007)	(0.008)	(0.015)	(0.011)	(0.015)
2,501-5,000	0.117	0.099	0.147	0.132	0.129
	(0.009)	(0.009)	(0.016)	(0.015)	(0.018)
5,001-10,000	0.177	0.167	0.140	0.199	0.203
	(0.009)	(0.011)	(0.017)	(0.018)	(0.018)
10,001-20,000	0.241	0.236	0.246	0.237	0.253
	(0.010)	(0.014)	(0.021)	(0.019)	(0.017)
More than 20,000	0.344	0.387	0.340	0.321	0.272
	(0.011)	(0.015)	(0.022)	(0.019)	(0.019)
Racial/ethnic identity: White	0.647	0.771	0.571	0.701	0.378
	(0.010)	(0.011)	(0.022)	(0.020)	(0.022)
Black	0.111	0.050	0.143	0.090	0.246
	(0.007)	(0.006)	(0.017)	(0.012)	(0.020)
Hispanic	0.119	0.069	0.144	0.112	0.222
	(0.005)	(0.006)	(0.015)	(0.014)	(0.014)
Asian	0.073	0.066	0.082	0.053	0.099
	(0.005)	(0.006)	(0.013)	(0.011)	(0.012)
Other	0.049	0.045	0.060	0.045	0.055
	(0.004)	(0.005)	(0.010)	(0.010)	(0.007)
FGLI status: Not first-gen, not low-income	0.487				
	(0.007)				
Low-income only	0.121				
	(0.005)				

	Full sample	Non-FGLI	LI only	FG only	FGLI
First-gen only	0.169 (0.006)				
First-gen, low-income	0.223 (0.007)				
Gender: Female	0.576 (0.009)	0.538 (0.012)	0.604 (0.027)	0.615 (0.022)	0.615 (0.020)
Student SAT/100	10.965 (0.039)	11.500 (0.054)	10.893 (0.075)	10.671 (0.082)	10.055 (0.083)
Student SAT: Imputation flag	0.002 (0.001)	*	*	*	*
HS GPA: C or below	0.002 (0.001)	*	*	*	0.004 (0.002)
C to B-	0.084 (0.005)	0.050 (0.005)	0.097 (0.012)	0.084 (0.011)	0.150 (0.016)
B- to B	0.124 (0.006)	0.113 (0.008)	0.108 (0.013)	0.128 (0.015)	0.156 (0.012)
B to A-	0.419 (0.007)	0.409 (0.011)	0.396 (0.023)	0.442 (0.021)	0.438 (0.017)
A- to A	0.370 (0.008)	0.427 (0.013)	0.395 (0.023)	0.343 (0.022)	0.252 (0.016)
N(Unweighted)	5,150	2,480	620	890	1,160
N(Weighted)	1,226,660	597,860	147,820	207,880	273,100

Note. All statistics were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

* Not reported to protect subgroups with fewer than 3 respondents.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table 3.3: OLS Regression Results from Models Estimating the Association between College Selectivity and Affective Engagement

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.090***	0.088***	0.064***	0.082***	0.067***
	(0.015)	(0.015)	(0.018)	(0.020)	(0.020)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	-0.128*		-0.041	-0.109	-0.040
	(0.055)		(0.059)	(0.068)	(0.059)
Hispanic	-0.203***		-0.157**	-0.151*	-0.158**
	(0.056)		(0.059)	(0.058)	(0.060)
Asian	-0.185**		-0.168*	-0.150*	-0.168*
	(0.067)		(0.070)	(0.071)	(0.070)
Other	-0.124+		-0.082	-0.080	-0.083
	(0.073)		(0.070)	(0.071)	(0.070)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.044	0.022	0.027	0.024	0.027
	(0.049)	(0.049)	(0.049)	(0.050)	(0.049)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.057	-0.064	-0.059	-0.062	-0.059
	(0.056)	(0.057)	(0.055)	(0.056)	(0.056)
5,001-10,000	-0.135*	-0.164**	-0.144*	-0.144*	-0.146*
	(0.059)	(0.060)	(0.058)	(0.060)	(0.058)
10,001-20,000	-0.188**	-0.224***	-0.192**	-0.185**	-0.194**
	(0.062)	(0.063)	(0.063)	(0.064)	(0.063)
More than 20,000	-0.234***	-0.280***	-0.255***	-0.253***	-0.253***
	(0.061)	(0.062)	(0.061)	(0.062)	(0.062)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		-0.110*	-0.089+	-0.084	-0.087
		(0.050)	(0.054)	(0.053)	(0.054)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.109*	-0.102*	-0.094+	-0.112*
		(0.050)	(0.049)	(0.049)	(0.049)
First-gen, low-income		-0.133**	-0.076+	-0.076+	-0.071
		(0.040)	(0.043)	(0.043)	(0.046)
Gender: Female			0.011	0.011	0.012
			(0.036)	(0.036)	(0.036)
Student SAT/100, mean-centered			-0.009	-0.010	-0.009
			(0.011)	(0.011)	(0.011)
Student SAT: Imputation flag			-0.643	-0.632	-0.632
			(0.693)	(0.702)	(0.698)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
C to B-			0.405	0.425	0.402
			(0.383)	(0.381)	(0.385)
B- to B			0.494	0.524	0.490
			(0.385)	(0.384)	(0.387)
B to A-			0.620	0.648+	0.618
			(0.380)	(0.379)	(0.382)
A- to A			0.787*	0.814*	0.784*
			(0.377)	(0.376)	(0.379)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				-0.089*	
				(0.044)	
Hispanic # Median SAT of college/100, mean-centered				0.002	
				(0.030)	
Asian # Median SAT of college/100, mean-centered				-0.046	
				(0.045)	
Other # Median SAT of college/100, mean-centered				-0.016	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
				(0.042)	
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.016
					(0.028)
First-gen only # Median SAT of college/100, mean-centered					-0.044
					(0.034)
First-gen, low-income # Median SAT of college/100, mean-centered					0.001
					(0.032)
Constant	0.191**	0.233***	-0.418	-0.451	-0.417
	(0.058)	(0.058)	(0.381)	(0.381)	(0.383)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.03	0.03	0.05	0.05	0.05

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table 3.4: OLS Regression Results from Models Estimating the Association between College Selectivity and Behavioral Engagement

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.067***	0.061**	0.066***	0.063**	0.057*
	(0.019)	(0.019)	(0.020)	(0.023)	(0.023)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	0.152*		0.190**	0.246**	0.199**
	(0.065)		(0.064)	(0.074)	(0.063)
Hispanic	0.104*		0.104*	0.095+	0.103*
	(0.047)		(0.051)	(0.051)	(0.052)
Asian	0.153*		0.154*	0.156+	0.156*
	(0.069)		(0.070)	(0.080)	(0.070)
Other	0.052		0.068	0.068	0.069
	(0.073)		(0.072)	(0.072)	(0.072)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.075	0.088+	0.055	0.055	0.059
	(0.053)	(0.053)	(0.053)	(0.054)	(0.053)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.057	-0.048	-0.066	-0.065	-0.069
	(0.071)	(0.072)	(0.072)	(0.073)	(0.072)
5,001-10,000	-0.120	-0.096	-0.128+	-0.132+	-0.127+
	(0.076)	(0.077)	(0.077)	(0.077)	(0.077)
10,001-20,000	-0.168+	-0.144+	-0.175*	-0.187*	-0.177*
	(0.086)	(0.084)	(0.085)	(0.085)	(0.085)
More than 20,000	-0.124	-0.094	-0.144+	-0.152+	-0.144+
	(0.085)	(0.084)	(0.085)	(0.085)	(0.083)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		0.096+	0.061	0.057	0.057
		(0.056)	(0.057)	(0.058)	(0.058)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.011	-0.032	-0.036	-0.046
		(0.047)	(0.048)	(0.048)	(0.048)
First-gen, low-income		0.053	-0.002	-0.003	0.021
		(0.052)	(0.055)	(0.056)	(0.060)
Gender: Female			0.134^{***}	0.134^{***}	0.135^{***}
			(0.039)	(0.039)	(0.038)
Student SAT/100, mean-centered			-0.019	-0.017	-0.019
			(0.014)	(0.013)	(0.014)
Student SAT: Imputation flag			0.023	0.029	0.033
			(0.460)	(0.464)	(0.461)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
C to B-			0.274	0.256	0.262
			(0.222)	(0.232)	(0.226)
B- to B			0.430^{+}	0.406	0.415^{+}
			(0.236)	(0.246)	(0.240)
B to A-			0.477^{*}	0.453^{+}	0.462^{*}
			(0.225)	(0.235)	(0.230)
A- to A			0.583^{*}	0.562^{*}	0.569^{*}
			(0.232)	(0.242)	(0.237)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				0.060	
				(0.045)	
Hispanic # Median SAT of college/100, mean-centered				-0.043	
				(0.037)	
Asian # Median SAT of college/100, mean-centered				0.001	
				(0.045)	
Other # Median SAT of college/100, mean-centered				0.013	

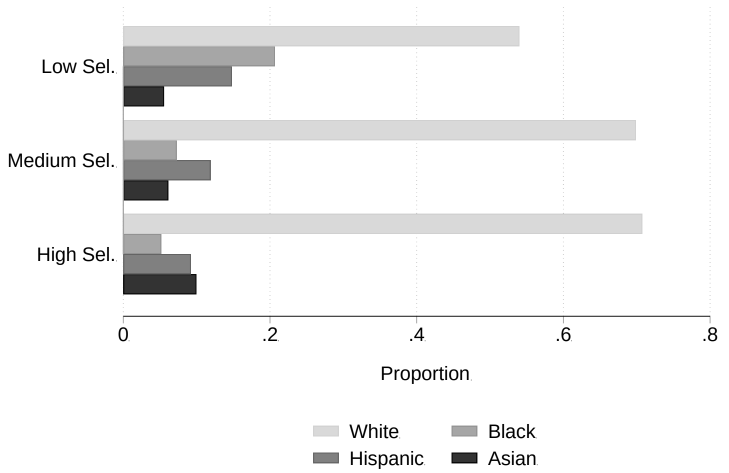
	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race) (0.056)	(5) Interaction (FGLI)
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.022
					(0.037)
First-gen only # Median SAT of college/100, mean-centered					-0.027
					(0.039)
First-gen, low-income # Median SAT of college/100, mean-centered					0.048
					(0.039)
Constant	0.036	0.031	-0.522*	-0.493*	-0.505*
	(0.080)	(0.084)	(0.239)	(0.247)	(0.242)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.02	0.01	0.03	0.03	0.03

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

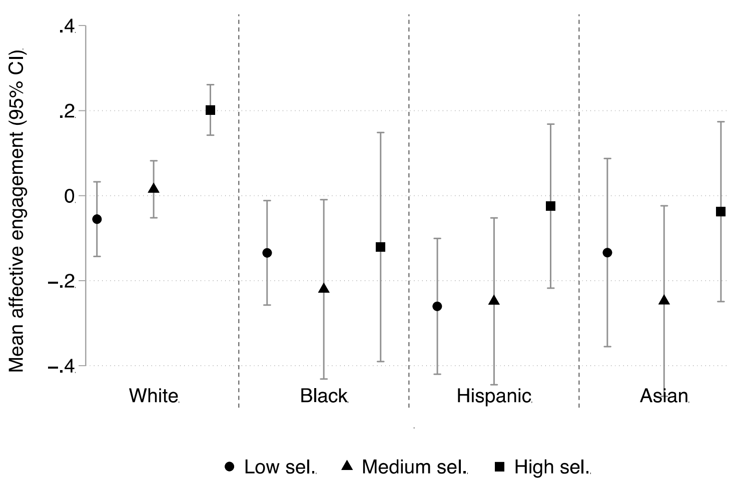
Study 3 Figures

Figure 3.1: Distribution of Students by College Selectivity and Race/ethnicity



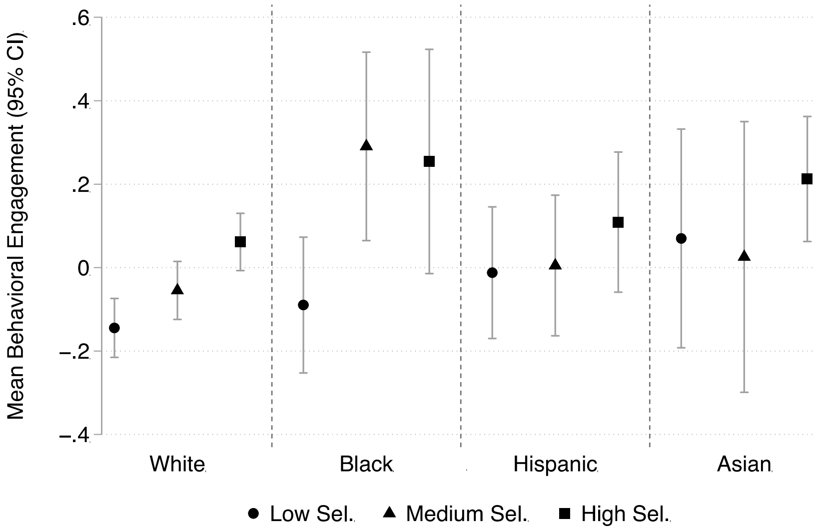
Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Figure 3.2: Mean Affective Engagement Scores by College Selectivity and Race/ethnicity



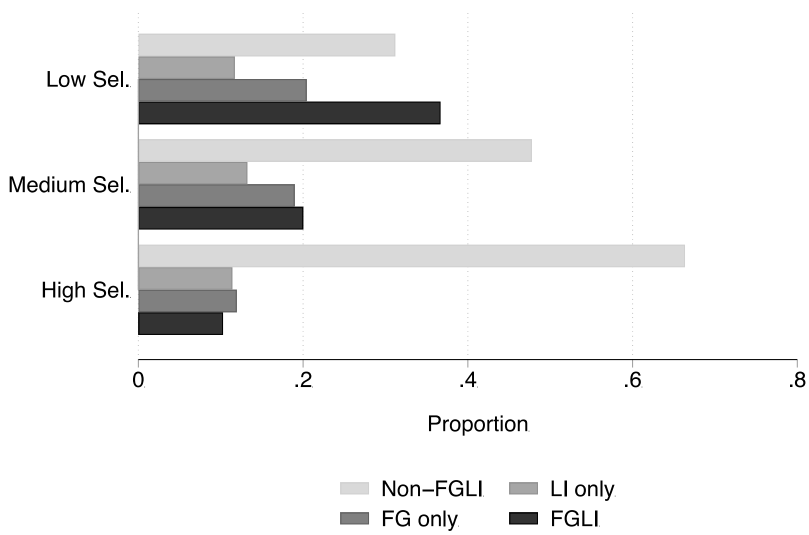
Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Figure 3.3: Mean Behavioral Engagement Scores by College Selectivity and Race/ethnicity



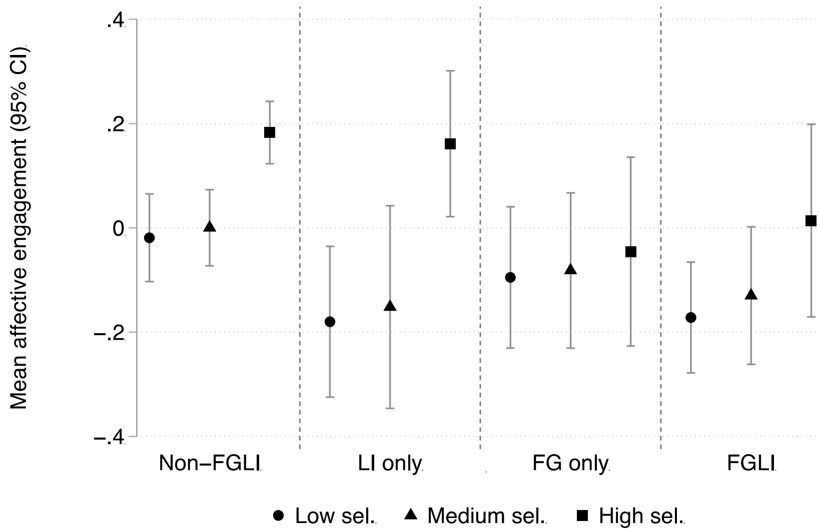
Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Figure 3.4: Distribution of Students by College Selectivity and FGLI Status



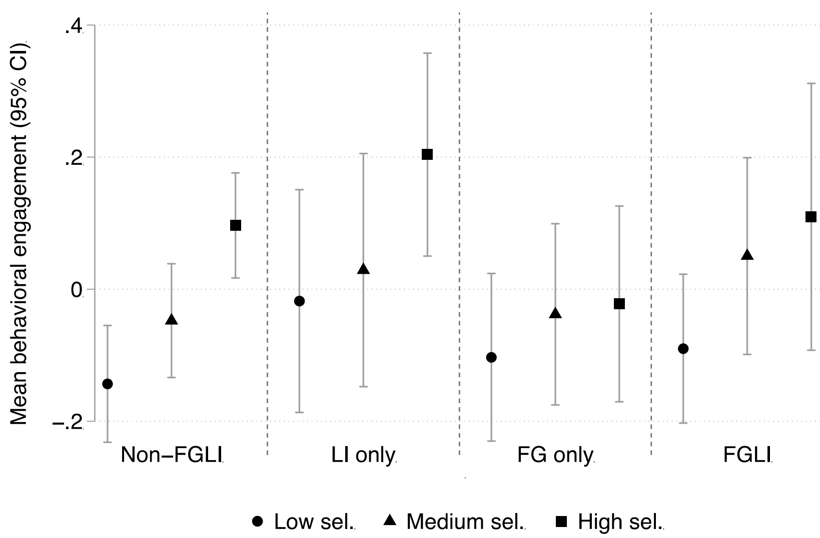
Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Figure 3.5: Mean Affective Engagement Scores by College Selectivity and FGLI Status



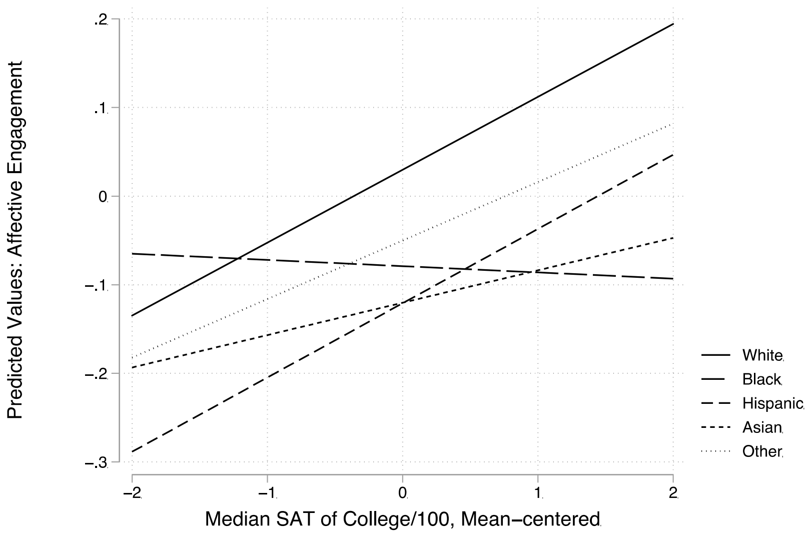
Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Figure 3.6: Mean Behavioral Engagement Scores by College Selectivity and FGLI Status



Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Figure 3.7: Regression-adjusted Affective Engagement Scores by College Selectivity and Race/ethnicity



Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

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Appendices

Study 1 Appendix Tables

Table A1.1: Creating the Analytic Sample

	1995 cohort	2003 cohort	2011 cohort
Weighted full sample	3,325,760	3,746,300	4,149,460
Weighted sample size after each restriction:			
1: responded to y1 and y6 survey waves	3,325,760	3,746,300	.
2: responded to all three survey waves	3,325,760	3,746,300	4,149,460
3: non-missing IPEDS	3,325,760	3,358,350	4,149,460
4: non-missing SAT/ACT	1,917,560	2,114,970	3,157,780
5: non-missing college selectivity	1,877,630	2,051,310	2,992,650
6: non-missing graduation	1,875,510	2,051,310	2,992,650
7: non-missing persistence	1,821,150	2,051,310	2,992,650
8: non-missing hs gpa	1,600,010	1,962,340	2,992,650
9: non-missing hs math	1,571,300	1,962,340	2,992,650
10: non-missing parental education	1,434,380	1,962,340	2,992,650
11: non-missing race	1,434,380	1,962,340	2,992,650
12: non-missing gender	1,434,380	1,962,340	2,992,650
13: non-missing age	1,434,380	1,962,340	2,992,650
14: did not attend college in Puerto Rico	1,433,570	1,946,370	2,992,650
Weighted analytic sample	1,433,570	1,946,370	2,992,650
Weighted analytic sample as % of full sample	43%	52%	72%
Unweighted full sample	12,090	16,680	19,840
Unweighted sample size after each restriction:			
1: responded to y1 and y6 survey waves	9,000	16,680	.
2: responded to all three survey waves	8,930	16,120	19,840
3: non-missing IPEDS	8,930	14,680	19,840
4: non-missing SAT/ACT	6,870	10,380	14,190
5: non-missing college selectivity	6,730	10,380	12,000
6: non-missing graduation	6,720	10,380	12,000
7: non-missing persistence	6,560	10,380	12,000
8: non-missing hs gpa	5,880	9,730	12,000
9: non-missing hs math	5,800	9,730	12,000
10: non-missing parental education	5,280	9,730	12,000
11: non-missing race	5,280	9,730	12,000

12: non-missing gender	5,280	9,730	12,000
13: non-missing age	5,280	9,730	12,000
14: did not attend college in Puerto Rico	5,270	9,650	12,000
Unweighted analytic sample	5,270	9,650	12,000
Unweighted analytic sample as % of full sample	44%	58%	60%

Notes. The proportion of respondents (weighted) that make it past the SAT restriction, after making it past the preceding restrictions, is 58% for the 1995 cohort and 62% and 76% for the 2003 and 2011 cohorts, respectively.

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A1.2: Creating the Analytic Sample: Two-Year and Less-Than-Two-Year Students Only

	1995 cohort	2003 cohort	2011 cohort
Weighted full sample	1,947,770	2,102,000	2,026,780
Weighted sample size after each restriction:			
1: responded to y1 and y6 survey waves	1,947,770	2,102,000	.
2: responded to all three survey waves	1,947,770	2,102,000	2,026,780
3: non-missing IPEDS	1,947,770	1,896,480	2,026,780
4: non-missing SAT/ACT	673,310	825,160	1,247,140
5: non-missing graduation	673,310	825,160	1,247,140
6: non-missing persistence	646,070	825,160	1,247,140
7: non-missing hs gpa	557,740	769,210	1,247,140
8: non-missing hs math	543,300	769,210	1,247,140
9: non-missing parental education	502,710	769,210	1,247,140
10: non-missing race	502,710	769,210	1,247,140
11: non-missing gender	502,710	769,210	1,247,140
12: non-missing age	502,710	769,210	1,247,140
13: did not attend college in Puerto Rico	502,710	766,750	1,247,140
Weighted analytic sample	502,710	766,750	1,247,140
Weighted analytic sample as % of full sample	26%	36%	62%

Notes. The proportion of respondents (weighted) that make it past the SAT restriction, after making it past the preceding restrictions, is 35% for the 1995 cohort and 44% and 62% for the 2003 and 2011 cohorts, respectively.

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A1.3: Creating the Analytic Sample: Four-Year Students Only

	1995 cohort	2003 cohort	2011 cohort
Weighted full sample	1,323,070	1,329,350	1,840,750
Weighted sample size after each restriction:			
1: responded to y1 and y6 survey waves	1,323,070	1,329,350	.
2: responded to all three survey waves	1,323,070	1,329,350	1,840,750
3: non-missing IPEDS	1,323,070	1,329,350	1,840,750
4: non-missing SAT/ACT	1,204,320	1,226,150	1,745,510
5: non-missing graduation	1,202,200	1,226,150	1,745,510
6: non-missing persistence	1,175,080	1,226,150	1,745,510
7: non-missing hs gpa	1,042,270	1,193,130	1,745,510
8: non-missing hs math	1,028,000	1,193,130	1,745,510
9: non-missing parental education	931,670	1,193,130	1,745,510
10: non-missing race	931,670	1,193,130	1,745,510
11: non-missing gender	931,670	1,193,130	1,745,510
12: non-missing age	931,670	1,193,130	1,745,510
13: did not attend college in Puerto Rico	930,850	1,179,620	1,745,510
Weighted analytic sample	930,850	1,179,620	1,745,510
Weighted analytic sample as % of full sample	70%	89%	95%

Notes. This table only includes four-year starters with valid Barron's selectivity data. The proportion of respondents (weighted) that make it past the SAT restriction, after making it past the preceding restrictions, is 91% for the 1995 cohort and 92% and 95% for the 2003 and 2011 cohorts, respectively.

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A1.4: Demographic Characteristics and College Outcomes by SAT/ACT-Taking, Restricted to Respondents with Non-Missing Values for Demographic and Outcome Variables

	1995 Cohort		2003 Cohort		2011 Cohort	
	Took SAT/ACT	Did not take SAT/ACT	Took SAT/ACT	Did not take SAT/ACT	Took SAT/ACT	Did not take SAT/ACT
Parental Education						
HS or Less	0.31	0.65	0.26	0.57	0.28	0.50
Some College	0.19	0.18	0.26	0.23	0.26	0.31
BA	0.27	0.13	0.25	0.13	0.23	0.12
More than BA	0.22	0.05	0.23	0.08	0.22	0.07
Dependent	0.94	0.43	0.93	0.35	0.89	0.45
Female	0.54	0.57	0.56	0.61	0.58	0.54
Underrepresented racial/ethnic minority	0.20	0.30	0.28	0.43	0.36	0.45
Age upon college entry	18.66	26.32	18.61	28.05	18.77	26.01
Selectivity of first college attended						
Very selective	0.16	0.01	0.12	0.00	0.12	0.00
Selective	0.16	0.01	0.14	0.01	0.16	0.01
Somewhat Selective	0.24	0.03	0.24	0.03	0.22	0.04
Nonselective	0.08	0.03	0.07	0.04	0.08	0.06
2-year or less	0.36	0.92	0.43	0.92	0.42	0.89
3-year persistence	0.78	0.34	0.71	0.35	0.73	0.40
6-year BA completion	0.47	0.04	0.46	0.05	0.48	0.07
N (Unweighted)	5,990	1,670	10,670	4,670	12,000	3,880
N (Weighted)	1,662,930	1,166,000	2,165,260	1,266,100	2,992,650	874,880
Proportion missing SAT (based on weighted n’s)		0.41		0.37		0.23

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A1.5: Illustrative Examples of Colleges at Each Selectivity Level

	Examples from California	Examples from Texas
Very selective	Claremont McKenna College University of California-Los Angeles Thomas Aquinas College	Baylor University Rice University The University of Texas at Dallas
Selective	San Diego State University University of California-Irvine University of La Verne	Saint Edward's University Texas State University University of Houston
Somewhat Selective	Dominican University of California San Jose State University Sonoma State University	Houston Baptist University Stephen F. Austin State University Texas Wesleyan University
Nonselective	California State University-Monterey Bay Humphreys University Woodbury University	Lamar University Southwestern Adventist University The University of Texas Rio Grande Valley
Two-year or Less	Lassen Community College Mission College San Jose City College	Central Texas College Hill College North Central Texas College

Note. To generate this table, I merged the 2014 Barron's selectivity ratings with data from IPEDS, a publicly available database of U.S. colleges and universities. I did not use BPS data to generate this list. I took a random sample of three colleges from each selectivity level in each state. I present examples from California and Texas because they are the two most populous states in the U.S. For two-year colleges, I only list public institutions because many of the private institutions in this category have very small enrollments (e.g., less than 200). Students from private two-year colleges are included in my analysis, but they make up a small share of my sample.

Table A1.6: Selected Cross-cohort Logistic Regression Results from Models Predicting BA Completion: Match x Cohort Specification

	Model 1: Main Analytic Sample
Match Status (Ref: Matched)	
Undermatched	0.556***
	(0.082)
Overmatched	2.234***
	(0.292)
Cohort (Ref: 1995)	
2003 Cohort	0.912
	(0.105)
2011 Cohort	0.960
	(0.111)
Match x Cohort Interaction	
Undermatch x 2003	0.906
	(0.154)
Undermatch x 2011	0.815
	(0.135)
Overmatch x 2003	1.023
	(0.151)
Overmatch x 2011	1.429*
	(0.216)
N (Unweighted)	26,920
N (Weighted)	6,372,580

Notes. Exponentiated coefficients (odds ratios); standard errors in parentheses. All models control for high school academic preparation and demographic characteristics.

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

* p<0.05, ** p<0.01, *** p<0.001

Table A1.7: Descriptive Statistics for Undermatched, Matched, and Overmatched Students: Weighted Means and Proportions

	Undermatched Students			Matched Students			Overmatched Students		
	1995 Cohort	2003 Cohort	2011 Cohort	1995 Cohort	2003 Cohort	2011 Cohort	1995 Cohort	2003 Cohort	2011 Cohort
Outcome Variable									
6-Year BA Completion	0.52	0.51	0.46	0.43	0.42	0.38	0.54	0.60	0.64
Academic Preparation Variables									
SAT/ACT	1,107.23	1,123.72	1,134.28	977.57	962.03	969.22	933.10	951.64	965.67
	(137.52)	(138.10)	(140.20)	(217.61)	(238.21)	(214.86)	(177.33)	(168.33)	(138.62)
HS GPA									
A- to A	0.47	0.63	0.44	0.30	0.33	0.23	0.20	0.29	0.18
B to A-	0.41	0.30	0.45	0.28	0.31	0.34	0.36	0.45	0.43
B- to B	0.07	0.06	0.08	0.17	0.17	0.14	0.24	0.15	0.19
C to B-	0.05	0.02	0.04	0.18	0.14	0.23	0.17	0.10	0.17
C and below	0.00	0.00	0.00	0.07	0.04	0.07	0.04	0.02	0.03
Highest Math Class Taken in HS									
Algebra or Geometry	0.03	0.04	0.06	0.17	0.13	0.14	0.12	0.08	0.08
Algebra 2	0.13	0.11	0.11	0.28	0.30	0.31	0.35	0.33	0.29
Trigonometry	0.23	0.17	0.10	0.13	0.17	0.09	0.20	0.24	0.14
Pre-Calculus	0.29	0.33	0.24	0.18	0.21	0.20	0.24	0.26	0.32
Calculus	0.32	0.35	0.47	0.24	0.20	0.27	0.09	0.10	0.18
Demographic Variables									
Most Educated Parent's Level of Education									
HS or Less / Don't Know	0.29	0.21	0.26	0.30	0.27	0.32	0.33	0.25	0.23
Some College	0.18	0.29	0.28	0.21	0.26	0.27	0.17	0.24	0.24
BA	0.31	0.27	0.26	0.27	0.23	0.20	0.27	0.27	0.26
More than BA	0.22	0.24	0.21	0.22	0.24	0.21	0.23	0.25	0.27
Dependent	0.95	0.95	0.87	0.96	0.92	0.88	0.97	0.96	0.94
Woman	0.54	0.53	0.56	0.54	0.58	0.57	0.57	0.58	0.60
Underrepresented Racial/Ethnic Minority	0.10	0.15	0.28	0.22	0.30	0.39	0.28	0.31	0.39
Age	18.46	18.57	18.87	18.46	18.63	18.89	18.48	18.46	18.49
	(0.94)	(0.94)	(1.67)	(0.69)	(1.08)	(1.69)	(1.54)	(0.91)	(1.02)
College Selectivity Variables									
Predicted College Selectivity									

	Undermatched Students			Matched Students			Overmatched Students		
Very Selective	0.28	0.23	0.23	0.20	0.14	0.13	0.00	0.00	0.00
Selective	0.26	0.28	0.28	0.11	0.10	0.11	0.15	0.12	0.12
Somewhat Selective	0.33	0.35	0.35	0.18	0.20	0.15	0.25	0.24	0.23
Nonselective	0.13	0.14	0.13	0.02	0.02	0.01	0.12	0.12	0.12
2-Year or Less	0.00	0.00	0.00	0.49	0.55	0.60	0.48	0.52	0.53
Selectivity of First College Attended									
Very Selective	0.00	0.00	0.00	0.20	0.14	0.13	0.26	0.22	0.22
Selective	0.13	0.11	0.12	0.11	0.10	0.11	0.28	0.28	0.28
Somewhat Selective	0.24	0.23	0.22	0.18	0.20	0.15	0.34	0.37	0.35
Nonselective	0.12	0.13	0.11	0.02	0.02	0.01	0.12	0.13	0.15
2-Year or Less	0.51	0.53	0.56	0.49	0.55	0.60	0.00	0.00	0.00
N (Unweighted)	1,170	2,350	3,150	1,950	4,260	5,520	2,160	3,040	3,330
N (Weighted)	406,570	527,200	808,120	594,790	871,780	1,326,400	432,213	547,380	858,140

Notes. Standard deviations for continuous variables are shown in parentheses.

[a] Median household income is reported in lieu of mean household income because the income distribution is right skewed.

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A1.8: Full Cohort-specific Logistic Regression Results from Models Predicting BA Completion, Various Model Specifications, Main Analytic Sample

	1995 Cohort			2003 Cohort			2011 Cohort		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Match Status (Reference: Matched)									
Undermatched	1.432*	0.572***	0.615***	1.464***	0.445***	0.500***	1.373***	0.349***	0.414***
	(0.192)	(0.0585)	(0.0665)	(0.110)	(0.0422)	(0.0473)	(0.101)	(0.0341)	(0.0413)
Overmatched	1.552**	2.324***	2.250***	2.001***	2.506***	2.416***	2.858***	3.820***	3.416***
	(0.229)	(0.283)	(0.286)	(0.141)	(0.220)	(0.213)	(0.258)	(0.392)	(0.351)
Academic Preparation Variables									
HS GPA (Reference: A to A-)									
C and Below	.	0.108***	0.121**	.	0.160***	0.198***	.	0.0658***	0.0867***
	.	(0.0650)	(0.0737)	.	(0.0598)	(0.0770)	.	(0.0189)	(0.0243)
C to B-	.	0.186***	0.207***	.	0.226***	0.255***	.	0.150***	0.177***
	.	(0.0522)	(0.0596)	.	(0.0366)	(0.0422)	.	(0.0236)	(0.0255)
B- to B	.	0.202***	0.225***	.	0.382***	0.402***	.	0.263***	0.297***
	.	(0.0495)	(0.0546)	.	(0.0478)	(0.0537)	.	(0.0335)	(0.0401)
B to A-	.	0.509***	0.548***	.	0.558***	0.571***	.	0.517***	0.542***
	.	(0.0840)	(0.0833)	.	(0.0513)	(0.0554)	.	(0.0474)	(0.0513)
SAT/ACT (Score Divided by 100)	.	1.388***	1.305***	.	1.493***	1.393***	.	1.522***	1.400***
	.	(0.0541)	(0.0413)	.	(0.0363)	(0.0369)	.	(0.0398)	(0.0376)
Highest Math Class Taken in HS (Reference: Calculus)									
Algebra or Geometry	.	0.481*	0.470*	.	0.213***	0.258***	.	0.175***	0.222***
	.	(0.167)	(0.159)	.	(0.0466)	(0.0537)	.	(0.0238)	(0.0337)
Algebra 2	.	0.502**	0.510**	.	0.309***	0.320***	.	0.301***	0.348***
	.	(0.114)	(0.107)	.	(0.0402)	(0.0424)	.	(0.0348)	(0.0424)
Trigonometry	.	0.681*	0.646*	.	0.561***	0.542***	.	0.760*	0.769
	.	(0.125)	(0.119)	.	(0.0712)	(0.0701)	.	(0.0997)	(0.106)

	1995 Cohort			2003 Cohort			2011 Cohort		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-Calculus	.	0.887	0.893	.	0.724**	0.720**	.	0.529***	0.528***
	.	(0.130)	(0.123)	.	(0.0875)	(0.0900)	.	(0.0603)	(0.0585)
Demographic Variables									
Most Educated Parent's Level of Education (Reference: More than BA)									
HS or Less / Don't Know	.	.	0.436***	.	.	0.518***	.	.	0.395***
	.	.	(0.0842)	.	.	(0.0591)	.	.	(0.0462)
Some College	.	.	0.518**	.	.	0.616***	.	.	0.482***
	.	.	(0.121)	.	.	(0.0612)	.	.	(0.0579)
BA	.	.	0.748*	.	.	0.864	.	.	0.850
	.	.	(0.105)	.	.	(0.0884)	.	.	(0.102)
Dependent (Reference: Financially Independent)			3.792***			2.947***			1.590
	.	.	(1.100)	.	.	(0.743)	.	.	(0.401)
Female (Reference: Male)	.	.	1.418*	.	.	1.403***	.	.	1.363***
	.	.	(0.202)	.	.	(0.106)	.	.	(0.114)
Underrepresented Racial/Ethnic Minority (Reference: Not URM)	.	.	0.719*	.	.	0.741***	.	.	0.740***
	.	.	(0.104)	.	.	(0.0607)	.	.	(0.0623)
Age Upon College Entry	.	.	0.931	.	.	0.751***	.	.	0.799***
	.	.	(0.0944)	.	.	(0.0387)	.	.	(0.0387)
Academic Preparation Controls?	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Demographic Controls?	No	No	Yes	No	No	Yes	No	No	Yes
Selectivity Controls?	No	No	No	No	No	No	No	No	No
Pseudo R2 [a]	0.00	0.17	0.19	0.01	0.24	0.26	0.04	0.29	0.33
BIC' [b]	-16.13	-1076.72	-1168.35	-178.56	-3104.05	-3298.08	-596.11	-4693.48	-5327.18
N (Unweighted)	5,270	5,270	5,270	9,650	9,650	9,650	12,000	12,000	12,000
N (Weighted)	1,433,570	1,433,570	1,433,570	1,946,370	1,946,370	1,946,370	2,992,650	2,992,650	2,992,650

Notes. Exponentiated coefficients (odds ratios); standard errors in parentheses.

[a] Estimated using unweighted data. [b] Estimated using unweighted data; lower BIC indicates superior model fit.

* p<0.05, ** p<0.01, *** p<0.001

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A1.9: Six-Year BA Completion Rates by Selectivity of First College Attended

	Full BPS Sample				Main Analytic Sample			
	1995 Cohort	2003 Cohort	2011 Cohort	Change from 1995 to 2011	1995 Cohort	2003 Cohort	2011 Cohort	Change from 1995 to 2011
Very Selective	0.79	0.84	0.88	+0.09	0.83	0.86	0.89	+0.06
Selective	0.66	0.73	0.80	+0.14	0.69	0.75	0.80	+0.11
Somewhat Selective	0.49	0.60	0.63	+0.14	0.53	0.63	0.65	+0.12
Nonselective	0.40	0.40	0.39	-0.01	0.48	0.48	0.45	-0.03
Two-Year or Less	0.08	0.09	0.11	+0.03	0.20	0.19	0.15	-0.05
N (Unweighted)	10,830	15,330	15,880	.	5,270	9,650	12,000	.
N (Weighted)	3,327,690	3,431,350	3,867,530	.	1,433,570	1,946,370	2,992,650	.

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01), 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09), and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A1.10: Full Cross-cohort Logistic Regression Results from Models Predicting BA Completion: 1995 Cohort vs. 2003 and 2011 Cohorts, Main Analytic Sample

	Undermatched Students	Matched Students	Overmatched Students
Academic Preparation Variables			
HS GPA (Reference: A to A-)			
C and Below	0.527	0.241***	0.252***
	(0.429)	(0.0834)	(0.0618)
C to B-	0.386*	0.364***	0.397***
	(0.151)	(0.0709)	(0.0471)
B- to B	0.363***	0.457***	0.525***
	(0.0723)	(0.0717)	(0.0646)
B to A-	0.690***	0.660***	0.702***
	(0.0712)	(0.0638)	(0.0635)
SAT (Score Divided by 100)	0.995	1.104*	1.117***
	(0.0413)	(0.0485)	(0.0326)
Highest Math Class Taken in HS (Reference: Calculus)			
Algebra or Geometry	0.540**	0.542**	0.570***
	(0.128)	(0.121)	(0.0849)
Algebra 2	0.857	0.655**	0.731**
	(0.159)	(0.101)	(0.0831)
Trigonometry	0.834	0.826	0.935
	(0.116)	(0.109)	(0.120)
Pre-Calculus	1.051	0.793	0.896
	(0.114)	(0.0981)	(0.104)

	Undermatched Students	Matched Students	Overmatched Students
Demographic Variables			
Most Educated Parent's Level of Education (Reference: More than BA)			
HS or Less / Don't Know	0.447***	0.443***	0.582***
	(0.0664)	(0.0592)	(0.0555)
Some College	0.576***	0.528***	0.582***
	(0.0815)	(0.0702)	(0.0531)
BA	1.033	0.804	0.830*
	(0.144)	(0.101)	(0.0764)
Dependent (Reference: Financially Independent)	1.995**	2.156***	1.493
	(0.450)	(0.483)	(0.504)
Female (Reference: Male)	1.351**	1.523***	1.286***
	(0.128)	(0.135)	(0.0843)
Underrepresented Racial/Ethnic Minority (Reference: Not URM)	0.639***	0.643***	0.819**
	(0.0784)	(0.0588)	(0.0606)
Age upon College Entry	0.839**	0.828**	0.847***
	(0.0516)	(0.0521)	(0.0378)
Selectivity of First College Attended (Reference: Somewhat Selective)			
Very Selective	.	2.114**	2.088***
	.	(0.502)	(0.256)
Selective	1.360	1.642***	1.457***
	(0.217)	(0.241)	(0.135)
Nonselective	0.512***	1.184	0.672**
	(0.0744)	(0.266)	(0.0843)

	Undermatched Students	Matched Students	Overmatched Students
Two-year or Less	0.155***	0.195***	.
	(0.0200)	(0.0340)	.
Cohort (Reference: 1995)			
2003 Cohort	0.980	1.115	1.111
	(0.146)	(0.162)	(0.0941)
2011 Cohort	0.965	1.215	1.594***
	(0.142)	(0.179)	(0.138)
Academic Preparation Controls?	Yes	Yes	Yes
Demographic Controls?	Yes	Yes	Yes
Selectivity Controls?	Yes	Yes	Yes
Pseudo R2 [a]	0.27	0.44	0.13
BIC' [b]	-2325.89	-6929.34	-1292.41
N (Unweighted)	6,660	11,730	8,530
N (Weighted)	1,741,890	2,792,970	1,837,730

Notes. Exponentiated coefficients (odds ratios); standard errors in parentheses.

[a] Estimated using unweighted data. [b] Estimated using unweighted data; lower BIC indicates superior model fit.

* p<0.05, ** p<0.01, *** p<0.001

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01) and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A1.11: Selected Cross-cohort Logistic Regression Results from Models Predicting BA Completion: 1995 Cohort vs. 2011 Cohort, Sample Includes Respondents with Missing Test Score Data

	Undermatched: Includes regular sample of undermatched students, as well as everyone who was missing an SAT/ACT score.	Matched: Includes regular sample of matched students, as well as everyone who was missing an SAT/ACT score.
Cohort (Ref: 1995)		
2011 Cohort	1.111	1.362*
	(0.140)	(0.178)
N (Unweighted)	9,770	12,910
N (Weighted)	3,231,550	3,938,050

Notes. Exponentiated coefficients (odds ratios); standard errors in parentheses. All models control for SAT score, parental education, dependent status, gender, race/ethnicity, age, and college selectivity. Respondents with mean-imputed SAT scores are flagged with a dummy variable. Models do not control for high school GPA or highest high school math course.

Source. U.S. Department of Education, National Center for Education Statistics, 1996/01 Beginning Postsecondary Students Longitudinal Study (BPS:96/01) and 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Study 2 Appendix Tables

Table A2.1: Variable Descriptions

Variable Name	**Variable Description**	**Variable Source**
Geographic Access: County-level	Categorical: High access, 2-yr. only, 4-yr. only, or low access. Respondents are coded as high access if they attended high school in a county with at least one public 2-yr. and one public 4-yr. college. They are coded as low access if they attended high school in a county with neither type of college. All others are coded as 2-yr. only or 4-yr. only.	Generated using respondents' most recent high school ID code (s2lasthsid or x1ncesid, HSLS restricted-use file) and data from CCD, PSS, and IPEDS.
Geographic Access: Radius-based	Categorical: High access, 2-yr. only, 4-yr. only, or low access. Respondents are coded as high access if they attended a high school that is within 30 miles of the nearest public two-year and public four-year college. They are coded as low access if their high school is not located within 30 miles of either type of college. All others are coded as 2-yr. only or 4-yr. only.	Generated using the same data as above, as well as NBER’s Zip Code Distance Database.
Distance Traveled	Continuous: Distance (in miles) between respondents’ high school and college. Distance is measured as the straight-line distance between the centroid of respondents’ high school zip code and the centroid of respondents’ college zip code. This variable is log-transformed in the regression models for RQ1 and RQ3.	Generated using the same data as above, as well as respondents’ IPEDS ID code, as of November 2013 (s3clgid, HSLS restricted-use file).
Distance Traveled Quintile	Categorical: This is a categorical measure of the distance traveled variable. Respondents in the first (lowest) quintile of distance traveled are assigned a value of 1, and so on.	Same as above.
Distance Traveled Flag	Binary: Indicates whether respondents have a top-coded value of 1,000 for the Distance Traveled variable (1=yes, 0=no).	Same as above.
Has First-year Loans	Binary: Received a Stafford or Perkins loan during the first year of college (1), or not (0).	Generated using the National Student Loan Data System (NSLDS) data file in the restricted-use version of the HSLS data.
First-year Loan Amount	Continuous: Dollar amount of Stafford and Perkins loans received during the first year of college. This	Same as above.

Variable Name	Variable Description	Variable Source
	variable is log-transformed in the regression analyses for RQ2 and RQ3.	
HS GPA	Continuous: Cumulative and honors-weighted high school GPA.	x3tgpawgt (HSLS public-use file)
HS GPA Flag	Binary: Indicates whether respondents have an imputed value for the HS GPA variable (1=yes, 0=no). To avoid dropping those with missing HS GPA data from my sample, I replaced missing HS GPA values with the median value for those with non-missing data, which was 3.	Same as above.
Racial/Ethnic Identity	Categorical: Asian, Black, Hispanic, White, or Other.	x1race (HSLS public-use file)
Gender Identity	Binary: Female (1) or male (0).	x1sex (HSLS public-use file)
Geographic Region of High School	Categorical: Northeast, Midwest, South, or West.	x4region (HSLS public-use file. I use data from prior waves if x4region is missing.)
Two-parent or single-parent household (2011)	Binary: As of 2011, respondents were living with two parents or guardians (1), or one parent or guardian (0).	x2parpattern (HSLS public-use file)
Socioeconomic Status (2011)	Continuous: NCES generated this variable using information about the income, education, and occupation of respondents' parents or guardians. This variable is standardized to have a mean of 0 and an SD of 1.	x4x2ses (HSLS public-use file)
College Type	Categorical: Indicates whether respondents’ first college (as of November 2013) was a 4-yr. public, 4-yr. private, 2-yr. public, 2-yr. private, or for-profit institution.	Generated using “sector” variable from IPEDS.
Balanced Repeated Replication (BRR) Weights	BRR weights adjust for the complex sampling design of the HSLS survey. They are used to compute the correct means, proportions, and standard errors.	w3w1w2stu001 - w3w1w2stu200 (HSLS public-use file)

Table A2.2: Descriptive Statistics by Geographic Access (Radius-based Measure)

	Full sample	Geog. access: High	Geog. access: 4-yr. only	Geog. access: 2-yr. only	Geog. access: Low
Took out a Stafford or Perkins loan, AY 1314	0.386	0.392	0.502	0.344	0.407
	(0.010)	(0.013)	(0.047)	(0.024)	(0.061)
Stafford & Perkins loans, AY 1314	2,101.494	2,160.608	2,612.111	1,833.635	2,115.884
	(55.886)	(75.262)	(267.428)	(153.061)	(383.350)
Radius-based access: High	0.710	1.000	0.000	0.000	0.000
	(0.022)	(.)	(.)	(.)	(.)
4-yr. only	0.028	0.000	1.000	0.000	0.000
	(0.007)	(.)	(.)	(.)	(.)
2-yr. only	0.213	0.000	0.000	1.000	0.000
	(0.021)	(.)	(.)	(.)	(.)
Low	0.048	0.000	0.000	0.000	1.000
	(0.011)	(.)	(.)	(.)	(.)
Distance traveled	125.612	125.755	110.277	125.391	133.468
	(4.483)	(5.901)	(15.337)	(10.325)	(23.344)
Distance traveled: Top-code flag	0.036	0.037	0.017	0.038	0.030
	(0.004)	(0.005)	(0.009)	(0.008)	(0.023)
Distance traveled is above the median	0.500	0.461	0.532	0.526	0.938
	(0.012)	(0.014)	(0.050)	(0.025)	(0.036)
HS GPA	3.167	3.155	3.252	3.183	3.204
	(0.017)	(0.022)	(0.053)	(0.033)	(0.084)
HS GPA: Imputation flag	0.035	0.037	0.011	0.031	0.034
	(0.008)	(0.010)	(0.022)	(0.009)	(0.030)
Race/ethnicity: White	0.548	0.544	0.783	0.493	0.711
	(0.013)	(0.019)	(0.038)	(0.036)	(0.047)
Asian	0.047	0.058	*	0.026	0.009
	(0.006)	(0.008)		(0.005)	(0.005)
Black	0.122	0.131	0.024	0.126	0.038
	(0.009)	(0.011)	(0.021)	(0.020)	(0.020)
Hispanic	0.200	0.186	0.104	0.272	0.139

	Full sample	Geog. access: High	Geog. access: 4-yr. only	Geog. access: 2-yr. only	Geog. access: Low
	(0.011)	(0.013)	(0.037)	(0.036)	(0.036)
Other	0.083	0.082	0.082	0.083	0.104
	(0.005)	(0.006)	(0.032)	(0.013)	(0.028)
Female	0.539	0.525	0.557	0.582	0.553
	(0.009)	(0.011)	(0.041)	(0.020)	(0.044)
HS region: South	0.374	0.332	0.331	0.536	0.295
	(0.008)	(0.015)	(0.111)	(0.049)	(0.096)
Northeast	0.199	0.243	0.243	0.077	0.057
	(0.007)	(0.015)	(0.111)	(0.028)	(0.045)
Midwest	0.202	0.203	0.359	0.162	0.278
	(0.009)	(0.013)	(0.121)	(0.031)	(0.087)
West	0.225	0.222	0.067	0.224	0.371
	(0.009)	(0.019)	(0.068)	(0.053)	(0.109)
SES	0.128	0.164	0.142	0.059	-0.094
	(0.019)	(0.024)	(0.086)	(0.040)	(0.059)
One-parent/guardian household	0.234	0.238	0.203	0.238	0.180
	(0.007)	(0.009)	(0.045)	(0.013)	(0.027)
1st college: 4-yr. public	0.439	0.432	0.657	0.452	0.349
	(0.011)	(0.014)	(0.054)	(0.024)	(0.058)
4-yr. private	0.181	0.196	0.154	0.147	0.134
	(0.008)	(0.009)	(0.034)	(0.018)	(0.036)
2-yr. public	0.347	0.335	0.152	0.382	0.477
	(0.013)	(0.016)	(0.034)	(0.027)	(0.086)
2-yr. private	0.001	0.002	*	*	*
	(0.000)	(0.001)			
For-profit	0.032	0.035	0.038	0.019	0.037
	(0.004)	(0.005)	(0.025)	(0.004)	(0.012)
HS locale: City	0.317	0.376	0.101	0.219	0.014
	(0.013)	(0.020)	(0.060)	(0.052)	(0.008)
Suburb	0.306	0.347	*	0.276	*
	(0.015)	(0.022)		(0.039)	
Town	0.109	0.054	0.407	0.198	0.352
	(0.011)	(0.013)	(0.117)	(0.035)	(0.099)

	Full sample	Geog. access: High	Geog. access: 4-yr. only	Geog. access: 2-yr. only	Geog. access: Low
Rural	0.267	0.223	0.488	0.306	0.628
	(0.013)	(0.018)	(0.118)	(0.046)	(0.100)
N(Unweighted)	9,000	6,710	300	1,610	380
N(Weighted)	2,178,330	1,546,320	61,790	464,730	105,490

Note. All statistics were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

* Not reported to protect subgroups with fewer than 3 respondents.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.3: Full OLS Regression Results from Models Estimating the Association between Geographic Access and Logged Distance Traveled

	(1) Geog. access only	(2) + controls	(3) + college type
County-level access (Ref: High)	0.000	0.000	0.000
	(.)	(.)	(.)
4-yr. only	0.120	0.009	-0.088
	(0.137)	(0.137)	(0.139)
2-yr. only	0.071	0.034	0.144
	(0.116)	(0.111)	(0.102)
Low	0.551^{***}	0.534^{***}	0.574^{***}
	(0.095)	(0.093)	(0.090)
HS GPA		0.495^{***}	0.080^{+}
		(0.044)	(0.041)
HS GPA: Imputation flag		-0.162	-0.219
		(0.252)	(0.203)
Racial/ethnic identity (Ref.: White)		0.000	0.000
		(.)	(.)
Asian		-0.298^{*}	-0.377^{***}
		(0.115)	(0.111)
Black		0.333^{**}	0.136
		(0.125)	(0.107)
Hispanic		-0.085	-0.170^{+}
		(0.091)	(0.087)
Other		-0.088	-0.149^{+}
		(0.087)	(0.079)
Gender Identity (Ref: Male)		0.000	0.000
		(.)	(.)
Female		-0.108	-0.085
		(0.068)	(0.057)
HS region (Ref: South)		0.000	0.000
		(.)	(.)
Northeast		0.005	-0.125
		(0.088)	(0.079)

	(1) Geog. access only	(2) + controls	(3) + college type
Midwest		0.070	0.019
		(0.084)	(0.078)
West		0.192^{+}	0.444***
		(0.113)	(0.109)
SES		0.477***	0.298***
		(0.046)	(0.041)
Two-parent/guardian household		0.000	0.000
		(.)	(.)
One-parent/guardian household		0.073	-0.001
		(0.093)	(0.084)
Sector of 1st college (Ref: 4-yr. public)			0.000
			(.)
4-yr. private			0.565***
			(0.096)
2-yr. public			-1.379***
			(0.086)
2-yr. private			0.419
			(0.329)
For-profit			-0.069
			(0.181)
Constant	3.437***	1.818***	3.529***
	(0.062)	(0.173)	(0.173)
N(Unweighted)	9,000	9,000	9,000
N(Weighted)	2,178,330	2,178,330	2,178,330
R-squared	0.01	0.13	0.28

Notes. All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.4: OLS Regression Results from Models Estimating the Association between Geographic Access and Distance Traveled, Using the Radius-based Measure of Geographic Access

	(1) Geog. access only	(2) + controls	(3) + college type
Radius-based access (Ref: High)	0.000	0.000	0.000
	(.)	(.)	(.)
4-yr. only	0.020	-0.000	-0.189
	(0.170)	(0.193)	(0.197)
2-yr. only	-0.003	0.026	0.089
	(0.138)	(0.124)	(0.111)
Low	0.938***	1.037***	1.159***
	(0.140)	(0.149)	(0.192)
N(Unweighted)	9,000	9,000	9,000
N(Weighted)	2,178,330	2,178,330	2,178,330
R-squared	0.01	0.14	0.29

Notes. Models 2 and 3 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), SES, and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Model 3 also controls for the sector and control of respondents' first college (ref: 4-yr. public). All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.5: OLS Regression Results from Models Estimating the Association between Geographic Access and Distance Traveled, with an Interaction between Geographic Access and SES

	(1) Geog. access only	(2) + controls	(3) + college type
County-level access (Ref: High)	0.000	0.000	0.000
	(.)	(.)	(.)
4-yr. only	0.069	0.026	-0.076
	(0.131)	(0.141)	(0.152)
2-yr. only	0.048	0.036	0.148
	(0.110)	(0.116)	(0.108)
Low	0.608***	0.566***	0.610***
	(0.086)	(0.095)	(0.092)
SES	0.683***	0.549***	0.381***
	(0.064)	(0.069)	(0.061)
County-level access (Ref: High) # SES	0.000	0.000	0.000
	(.)	(.)	(.)
4-yr. only # SES	-0.090	-0.093	-0.077
	(0.154)	(0.161)	(0.166)
2-yr. only # SES	0.007	-0.014	-0.025
	(0.103)	(0.106)	(0.092)
Low # SES	-0.364***	-0.340***	-0.381***
	(0.099)	(0.096)	(0.082)
N(Unweighted)	9,000	9,000	9,000
N(Weighted)	2,178,330	2,178,330	2,178,330
R-squared	0.09	0.14	0.29

Notes. Models 2 and 3 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Model 3 also controls for the sector and control of respondents' first college (ref: 4-yr. public). All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.6: Full LPM and OLS Regression Results from Models Estimating the Association between Distance Traveled and Student Debt

	(1) LPM: Dist. traveled only	(2) + controls	(3) + college type	(4) OLS: Dist. traveled only	(5) + controls	(6) + college type
Distance traveled quintile (Ref: 1st quintile)	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
2nd quintile	0.020	0.040	0.009	0.197	0.374	0.106
	(0.037)	(0.033)	(0.031)	(0.311)	(0.283)	(0.267)
3rd quintile	0.181***	0.175***	0.082**	1.594***	1.540***	0.735***
	(0.028)	(0.027)	(0.026)	(0.233)	(0.230)	(0.214)
4th quintile	0.313***	0.311***	0.172***	2.741***	2.721***	1.516***
	(0.027)	(0.027)	(0.026)	(0.228)	(0.233)	(0.221)
5th (highest) quintile	0.280***	0.295***	0.124***	2.446***	2.572***	1.086***
	(0.026)	(0.027)	(0.027)	(0.218)	(0.226)	(0.225)
Distance traveled: Top-code flag=0	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Distance traveled: Top-code flag=1	-0.156**	-0.153*	-0.180**	-1.344**	-1.318*	-1.552**
	(0.057)	(0.065)	(0.065)	(0.488)	(0.555)	(0.554)
HS GPA		0.036**	-0.036**		0.308**	-0.313**
		(0.013)	(0.013)		(0.113)	(0.107)
HS GPA: Imputation flag		-0.075*	-0.092**		-0.640*	-0.792**
		(0.032)	(0.033)		(0.274)	(0.287)
Racial/ethnic identity (Ref.: White)		0.000	0.000		0.000	0.000
		(.)	(.)		(.)	(.)
Asian		-0.083**	-0.119***		-0.720**	-1.034***
		(0.030)	(0.031)		(0.257)	(0.264)
Black		0.133***	0.096**		1.174***	0.854***
		(0.029)	(0.029)		(0.253)	(0.246)
Hispanic		-0.030	-0.060**		-0.251	-0.512**
		(0.021)	(0.019)		(0.176)	(0.164)
Other		0.045+	0.027		0.397+	0.243
		(0.026)	(0.026)		(0.220)	(0.214)

	(1) LPM: Dist. traveled only	(2) + controls	(3) + college type	(4) OLS: Dist. traveled only	(5) + controls	(6) + college type
Gender Identity (Ref: Male)		0.000	0.000		0.000	0.000
		(.)	(.)		(.)	(.)
Female		0.057***	0.059***		0.492***	0.505***
		(0.015)	(0.014)		(0.129)	(0.120)
HS region (Ref: South)		0.000	0.000		0.000	0.000
		(.)	(.)		(.)	(.)
Northeast		0.209***	0.165***		1.806***	1.423***
		(0.024)	(0.025)		(0.206)	(0.212)
Midwest		0.148***	0.132***		1.268***	1.128***
		(0.021)	(0.020)		(0.181)	(0.169)
West		-0.051*	0.000		-0.424+	0.015
		(0.026)	(0.022)		(0.221)	(0.189)
SES		-0.055***	-0.078***		-0.465***	-0.664***
		(0.013)	(0.011)		(0.108)	(0.098)
Two-parent/guardian household		0.000	0.000		0.000	0.000
		(.)	(.)		(.)	(.)
One-parent/guardian household		0.022	0.008		0.179	0.050
		(0.022)	(0.020)		(0.186)	(0.171)
Sector of 1st college (Ref: 4-yr. public)			0.000			0.000
			(.)			(.)
4-yr. private			0.145***			1.269***
			(0.022)			(0.193)
2-yr. public			-0.307***			-2.658***
			(0.021)			(0.177)
2-yr. private			-0.013			-0.080
			(0.169)			(1.478)
For-profit			0.050			0.542
			(0.064)			(0.558)
Constant	0.233***	0.016	0.431***	1.938***	0.078	3.660***
	(0.019)	(0.040)	(0.048)	(0.159)	(0.340)	(0.402)
N(Unweighted)	9,000	9,000	9,000	9,000	9,000	9,000
N(Weighted)	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330

	(1) LPM: Dist. traveled only	(2) + controls	(3) + college type	(4) OLS: Dist. traveled only	(5) + controls	(6) + college type
R-squared	0.07	0.14	0.22	0.07	0.14	0.23

Notes. All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.7: Truncated Regression Results from Models Estimating the Association between Distance Traveled and Logged Student Debt

	(1) Truncated: Dist. traveled only	(2) + controls	(3) + college type
Distance traveled quintile (Ref: 1st quintile)	0.000 (.)	0.000 (.)	0.000 (.)
2nd quintile	0.138* (0.061)	0.137* (0.063)	0.111+ (0.059)
3rd quintile	0.197*** (0.052)	0.191*** (0.053)	0.133** (0.048)
4th quintile	0.238*** (0.055)	0.238*** (0.056)	0.169** (0.052)
5th (highest) quintile	0.224*** (0.056)	0.222*** (0.058)	0.140** (0.053)
N(Unweighted)	3,540	3,540	3,540
N(Weighted)	840,080	840,080	840,080

Notes. These models are restricted to those with non-zero debt. Models 2 and 3 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), SES, and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Models 3 also controls for the sector and control of respondents' first college (ref: 4-yr. public). All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.8: LPM, OLS, and Truncated Regression Results from Models Estimating the Association between Distance Traveled and Student Debt, with an Interaction between Distance Traveled and SES

	(1) LPM: Dist. traveled only	(2) + controls	(3) + college type	(4) OLS: Dist. traveled only	(5) + controls	(6) + college type	(7) Truncated: Dist. traveled only	(8) + controls	(9) + college type
Distance traveled quintile (Ref: 1st quintile)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2nd quintile	0.020	0.039	0.010	0.199	0.363	0.113	0.132*	0.132*	0.106^{+}
	(0.035)	(0.032)	(0.030)	(0.300)	(0.269)	(0.257)	(0.060)	(0.062)	(0.058)
3rd quintile	0.182***	0.168***	0.078**	1.594***	1.479***	0.694**	0.188***	0.184***	0.128**
	(0.028)	(0.026)	(0.025)	(0.232)	(0.223)	(0.211)	(0.051)	(0.052)	(0.047)
4th quintile	0.355***	0.334***	0.197***	3.101***	2.927***	1.729***	0.233***	0.238***	0.170**
	(0.031)	(0.029)	(0.028)	(0.263)	(0.249)	(0.239)	(0.055)	(0.055)	(0.051)
5th (highest) quintile	0.332***	0.313***	0.139***	2.888***	2.728***	1.218***	0.215***	0.217***	0.134*
	(0.030)	(0.029)	(0.028)	(0.258)	(0.241)	(0.239)	(0.060)	(0.061)	(0.057)
SES	-0.003	0.008	-0.027	-0.008	0.096	-0.211	0.092	0.101	0.093
	(0.024)	(0.025)	(0.023)	(0.197)	(0.208)	(0.195)	(0.070)	(0.076)	(0.071)
Distance traveled quintile (Ref: 1st quintile) # SES	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2nd quintile # SES	0.005	-0.009	0.015	0.028	-0.094	0.121	-0.050	-0.054	-0.056
	(0.042)	(0.039)	(0.035)	(0.357)	(0.329)	(0.300)	(0.091)	(0.094)	(0.088)
3rd quintile # SES	0.005	-0.019	-0.023	0.026	-0.181	-0.218	-0.088	-0.098	-0.092
	(0.032)	(0.035)	(0.031)	(0.272)	(0.301)	(0.269)	(0.078)	(0.082)	(0.076)
4th quintile # SES	-0.127**	-0.153***	-0.137***	-1.118***	-1.339***	-1.198***	-0.108	-0.118	-0.109
	(0.039)	(0.037)	(0.034)	(0.328)	(0.314)	(0.290)	(0.081)	(0.086)	(0.081)
5th (highest) quintile # SES	-0.108**	-0.113**	-0.091*	-0.948**	-0.990**	-0.793*	-0.090	-0.096	-0.081
	(0.041)	(0.042)	(0.041)	(0.344)	(0.350)	(0.345)	(0.092)	(0.096)	(0.089)
N(Unweighted)	9,000	9,000	9,000	9,000	9,000	9,000	3,540	3,540	3,540
N(Weighted)	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	840,080	840,080	840,080
R-squared	0.08	0.14	0.23	0.08	0.15	0.23			

Notes. Models 7-9 are restricted to those with non-zero debt. Models 2-3, 5-6, and 8-9 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Models 3, 6, and 9 also control for the sector and control of respondents' first college (ref: 4-yr. public). All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.9: Full LPM and OLS Regression Results from Models Estimating the Association between Geographic Access and Student Debt

	(1) LPM: Geog. access only	(2) + controls	(3) + dist. traveled	(4) + college type	(5) OLS: Geog. access only	(6) + controls	(7) + dist. traveled	(8) + college type
County-level access (Ref: High)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
4-yr. only	0.105^{**}	0.056^{+}	0.031	0.033	0.890^{**}	0.472^{+}	0.255	0.272
	(0.036)	(0.031)	(0.027)	(0.027)	(0.312)	(0.265)	(0.232)	(0.231)
2-yr. only	-0.015	-0.023	0.006	-0.005	-0.135	-0.202	0.049	-0.047
	(0.029)	(0.022)	(0.020)	(0.020)	(0.251)	(0.185)	(0.172)	(0.167)
Low	0.050^{+}	0.038	0.048^{+}	0.015	0.423	0.323	0.414^{+}	0.127
	(0.030)	(0.027)	(0.025)	(0.026)	(0.258)	(0.229)	(0.216)	(0.224)
HS GPA		0.071^{***}	-0.034^{*}	-0.036^{**}		0.607^{***}	-0.298^{**}	-0.310^{**}
		(0.013)	(0.014)	(0.013)		(0.112)	(0.114)	(0.109)
HS GPA: Imputation flag		-0.075^{*}	-0.089^{**}	-0.090^{**}		-0.647^{*}	-0.765^{**}	-0.768^{**}
		(0.034)	(0.033)	(0.033)		(0.286)	(0.285)	(0.286)
Racial/ethnic identity (Ref.: White)		0.000	0.000	0.000		0.000	0.000	0.000
		(.)	(.)	(.)		(.)	(.)	(.)
Asian		-0.115^{***}	-0.134^{***}	-0.117^{***}		-0.995^{***}	-1.165^{***}	-1.012^{***}
		(0.029)	(0.032)	(0.031)		(0.249)	(0.270)	(0.265)
Black		0.152^{***}	0.102^{***}	0.098^{***}		1.344^{***}	0.909^{***}	0.875^{***}
		(0.033)	(0.030)	(0.028)		(0.281)	(0.257)	(0.243)
Hispanic		-0.049^{*}	-0.070^{***}	-0.057^{**}		-0.415^{*}	-0.601^{***}	-0.485^{**}
		(0.021)	(0.020)	(0.019)		(0.179)	(0.171)	(0.165)
Other		0.040	0.025	0.029		0.354	0.222	0.256
		(0.027)	(0.026)	(0.025)		(0.228)	(0.218)	(0.212)
Gender Identity (Ref: Male)		0.000	0.000	0.000		0.000	0.000	0.000
		(.)	(.)	(.)		(.)	(.)	(.)
Female		0.056^{***}	0.062^{***}	0.059^{***}		0.481^{***}	0.526^{***}	0.501^{***}
		(0.016)	(0.014)	(0.014)		(0.134)	(0.121)	(0.119)

	(1) LPM: Geog. access only	(2) + controls	(3) + dist. traveled	(4) + college type	(5) OLS: Geog. access only	(6) + controls	(7) + dist. traveled	(8) + college type
HS region (Ref: South)		0.000	0.000	0.000		0.000	0.000	0.000
		(.)	(.)	(.)		(.)	(.)	(.)
Northeast		0.196***	0.164***	0.168***		1.696***	1.411***	1.449***
		(0.026)	(0.025)	(0.026)		(0.224)	(0.217)	(0.219)
Midwest		0.154***	0.141***	0.132***		1.319***	1.206***	1.125***
		(0.022)	(0.020)	(0.019)		(0.189)	(0.172)	(0.167)
West		-0.056*	0.009	0.003		-0.473*	0.088	0.038
		(0.025)	(0.022)	(0.022)		(0.214)	(0.187)	(0.190)
SES		-0.023+	-0.068***	-0.077***		-0.190+	-0.578***	-0.657***
		(0.013)	(0.012)	(0.012)		(0.110)	(0.099)	(0.099)
Two-parent/guardian household		0.000	0.000	0.000		0.000	0.000	0.000
		(.)	(.)	(.)		(.)	(.)	(.)
One-parent/guardian household		0.020	0.001	0.008		0.153	-0.004	0.049
		(0.023)	(0.020)	(0.020)		(0.200)	(0.174)	(0.171)
Sector of 1st college (Ref: 4-yr. public)			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
4-yr. private			0.136***	0.146***			1.193***	1.273***
			(0.023)	(0.022)			(0.196)	(0.194)
2-yr. public			-0.358***	-0.305***			-3.106***	-2.644***
			(0.019)	(0.022)			(0.158)	(0.180)
2-yr. private			0.019	-0.011			0.192	-0.064
			(0.175)	(0.169)			(1.531)	(1.479)
For-profit			0.035	0.051			0.414	0.551
			(0.065)	(0.064)			(0.570)	(0.556)
Distance traveled quintile (Ref: 1st quintile)				0.000				0.000

	(1) LPM: Geog. access only	(2) + controls	(3) + dist. traveled	(4) + college type	(5) OLS: Geog. access only	(6) + controls	(7) + dist. traveled	(8) + college type
				(.)				(.)
2nd quintile				0.008				0.096
				(0.031)				(0.262)
3rd quintile				0.080**				0.713**
				(0.027)				(0.223)
4th quintile				0.170***				1.499***
				(0.027)				(0.227)
5th (highest) quintile				0.123***				1.078***
				(0.027)				(0.225)
Distance traveled: Top-code flag=0				0.000				0.000
				(.)				(.)
Distance traveled: Top-code flag=1				-0.180**				-1.554**
				(0.065)				(0.553)
Constant	0.375***	0.066	0.500***	0.425***	3.198***	0.533	4.286***	3.612***
	(0.019)	(0.043)	(0.047)	(0.047)	(0.165)	(0.363)	(0.394)	(0.401)
N(Unweighted)	9,000	9,000	9,000	9,000	9,000	9,000	9,000	9,000
N(Weighted)	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330
R-squared	0.00	0.08	0.20	0.22	0.00	0.08	0.21	0.23

Notes. All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

* p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.10: Truncated Regression Results from Models Estimating the Association between Geographic Access and Student Debt

	(1) Truncated: County access only	(2) + controls	(3) + college type	(4) + dist. traveled
County-level access (Ref: High)	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
4-yr. only	-0.018	-0.006	0.010	0.015
	(0.034)	(0.035)	(0.034)	(0.035)
2-yr. only	-0.020	-0.011	0.018	0.007
	(0.034)	(0.033)	(0.033)	(0.032)
Low	-0.008	0.014	0.043	0.019
	(0.037)	(0.036)	(0.035)	(0.034)
N(Unweighted)	3,540	3,540	3,540	3,540
N(Weighted)	840,080	840,080	840,080	840,080

Notes. These models are restricted to those with non-zero debt. Models 2, 3, and 4 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), SES, and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Model 3 also controls for the sector and control of respondents' first college (ref: 4-yr. public). Model 4 also controls for the logged distance between students' high schools and colleges. All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.11: LPM, OLS, and Truncated Regression Results from Models Estimating the Association between Geographic Access and Student Debt, Using the Radius-based Measure of Geographic Access

	(1) LPM: Geog. access only	(2) + controls	(3) + college type	(4) + dist. traveled	(5) OLS: Geog. access only	(6) + controls	(7) + college type	(8) + dist. traveled	(9) Truncated: Geog. access only	(10) + controls	(11) + college type	(12) + dist. traveled
Radius-based access (Ref: High)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
4-yr. only	0.110*	0.071	0.022	0.027	0.903*	0.573	0.145	0.189	-0.079	-0.071	-0.065	-0.055
	(0.049)	(0.041)	(0.041)	(0.040)	(0.417)	(0.344)	(0.349)	(0.338)	(0.044)	(0.046)	(0.044)	(0.045)
2-yr. only	-0.048	-0.016	0.001	-0.008	-0.431	-0.157	-0.007	-0.079	-0.061	-0.052	-0.016	-0.025
	(0.030)	(0.024)	(0.022)	(0.022)	(0.256)	(0.208)	(0.189)	(0.188)	(0.036)	(0.037)	(0.035)	(0.035)
Low	0.015	0.041	0.073*	0.007	0.093	0.318	0.597*	0.018	-0.090	-0.082	-0.040	-0.075
	(0.065)	(0.048)	(0.035)	(0.039)	(0.559)	(0.416)	(0.302)	(0.332)	(0.085)	(0.083)	(0.082)	(0.083)
Sector of 1st college (Ref: 4-yr. public)			0.000	0.000			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)			(.)	(.)
4-yr. private			0.135***	0.145***			1.181***	1.267***			0.042	0.049*
			(0.023)	(0.022)			(0.198)	(0.195)			(0.023)	(0.023)
2-yr. public			-0.360***	-0.306***			-3.126***	-2.654***			- 0.337***	- 0.291***
			(0.019)	(0.021)			(0.158)	(0.177)			(0.045)	(0.047)
2-yr. private			0.016	-0.013			0.173	-0.080			0.056	0.038
			(0.177)	(0.170)			(1.549)	(1.484)			(0.295)	(0.293)
For-profit			0.033	0.049			0.394	0.537			0.214**	0.233**
			(0.065)	(0.064)			(0.571)	(0.558)			(0.067)	(0.071)
Distance traveled quintile (Ref: 1st quintile)				0.000				0.000				0.000
				(.)				(.)				(.)
2nd quintile				0.009				0.108				0.110
				(0.031)				(0.267)				(0.058)
3rd quintile				0.082**				0.731***				0.134**
				(0.026)				(0.214)				(0.046)
4th quintile				0.171***				1.508***				0.172**
				(0.027)				(0.224)				(0.052)
5th (highest) quintile				0.123***				1.083***				0.143**
				(0.027)				(0.226)				(0.053)
N(Unweighted)	9,000	9,000	9,000	9,000	9,000	9,000	9,000	9,000	3,540	3,540	3,540	3,540
N(Weighted)	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	840,080	840,080	840,080	840,080
R-squared	0.00	0.08	0.20	0.22	0.00	0.08	0.21	0.23				

Notes. Models 9-12 are restricted to those with non-zero debt. Models 2-4, 6-8, and 10-12 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), SES, and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Models 3, 7, and 11 also control for the sector and control of respondents' first college (ref: 4-yr. public). Models 4, 8, and 12 also control for the logged distance between students’ high schools and colleges. All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

$^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Table A2.12: LPM, OLS, and Truncated Regression Results from Models Estimating the Association between Geographic Access and Student Debt, with an Interaction between Geographic Access and SES

	(1) LPM: Geog. access only	(2) + controls	(3) + college type	(4) + dist. traveled	(5) OLS: Geog. access only	(6) + controls	(7) + college type	(8) + dist. traveled	(9) Truncated: Geog. access only	(10) + controls	(11) + college type	(12) + dist. traveled
County-level access (Ref: High)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
4-yr. only	0.124**	0.069	0.043	0.043	1.038**	0.575	0.348	0.349	-0.026	-0.014	0.009	0.011
	(0.043)	(0.037)	(0.033)	(0.033)	(0.370)	(0.316)	(0.282)	(0.285)	(0.038)	(0.039)	(0.039)	(0.040)
2-yr. only	-0.015	-0.019	0.010	-0.001	-0.138	-0.167	0.091	-0.007	-0.019	-0.007	0.026	0.015
	(0.031)	(0.024)	(0.022)	(0.021)	(0.262)	(0.205)	(0.185)	(0.180)	(0.037)	(0.036)	(0.036)	(0.036)
Low	0.055	0.043	0.055*	0.022	0.462	0.369	0.471*	0.185	-0.004	0.016	0.050	0.026
	(0.031)	(0.028)	(0.026)	(0.027)	(0.263)	(0.240)	(0.221)	(0.229)	(0.039)	(0.038)	(0.037)	(0.037)
SES	0.011	-0.003	-0.045*	-0.058**	0.101	-0.019	-0.376*	-0.489**	0.031	0.032	0.046	0.035
	(0.018)	(0.020)	(0.018)	(0.018)	(0.154)	(0.172)	(0.159)	(0.156)	(0.031)	(0.033)	(0.033)	(0.033)
County-level access (Ref: High) # SES	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
4-yr. only # SES	-0.087	-0.065	-0.061	-0.052	-0.711	-0.530	-0.492	-0.410	0.059	0.060	0.022	0.034
	(0.045)	(0.043)	(0.044)	(0.044)	(0.381)	(0.365)	(0.373)	(0.378)	(0.066)	(0.066)	(0.066)	(0.066)
2-yr. only # SES	0.000	-0.024	-0.028	-0.024	-0.002	-0.209	-0.249	-0.210	-0.014	-0.019	-0.050	-0.046
	(0.031)	(0.032)	(0.028)	(0.028)	(0.264)	(0.273)	(0.242)	(0.238)	(0.042)	(0.041)	(0.040)	(0.039)
Low # SES	-0.054	-0.046	-0.057	-0.047	-0.462	-0.390	-0.489	-0.399	-0.001	-0.003	-0.045	-0.033
	(0.033)	(0.032)	(0.029)	(0.029)	(0.288)	(0.278)	(0.253)	(0.253)	(0.056)	(0.056)	(0.052)	(0.051)
N(Unweighted)	9,000	9,000	9,000	9,000	9,000	9,000	9,000	9,000	3,540	3,540	3,540	3,540
N(Weighted)	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	2,178,330	840,080	840,080	840,080	840,080
R-squared	0.01	0.08	0.20	0.22	0.01	0.08	0.21	0.23				

Notes. Models 2-4, 6-8, and 10-12 control for the following variables: HS GPA, race/ethnicity (ref: White), gender (ref: male), HS region (ref: South), and whether the respondent was raised in a single-parent or two-parent household (ref: two-parent). Models 3, 7, and 11 also control for the sector and control of respondents' first college (ref: 4-yr. public). Finally, Models 4, 8, and 12 control for the logged distance between students' high schools and colleges. All models were estimated using the appropriate survey weights. Survey-weighted standard errors are in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source. U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09).

Study 2 Appendix Figures

Figure A2.1: Data Processing Procedure for Distance Traveled Variable

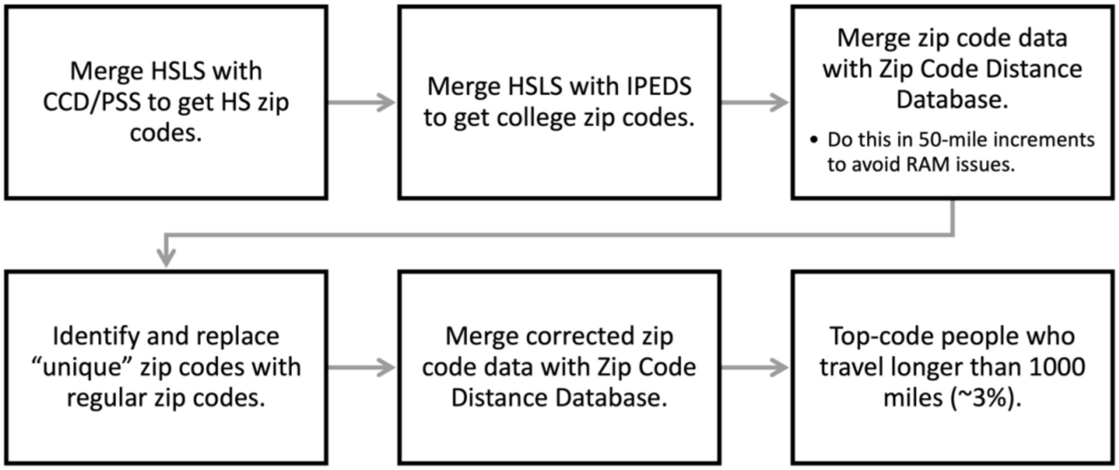
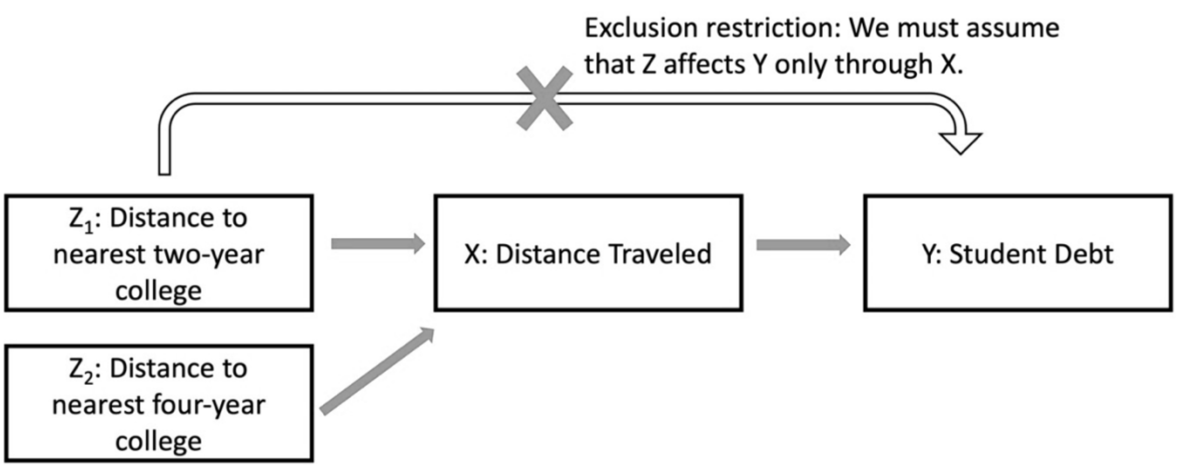


Figure A2.2: Potential Instrumental Variable (IV) Research Design



Study 3 Appendix Tables

Table A3.1: Multilevel Regression Results from Models Estimating the Association between College Selectivity and Affective Engagement

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.086^{***}	0.086^{***}	0.058^{***}	0.078^{***}	0.064^{***}
	(0.013)	(0.014)	(0.015)	(0.018)	(0.018)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	-0.167^{***}		-0.085^{+}	-0.125^{*}	-0.087^{+}
	(0.047)		(0.049)	(0.054)	(0.049)
Hispanic	-0.125^{**}		-0.082^{+}	-0.078^{+}	-0.083^{+}
	(0.043)		(0.044)	(0.044)	(0.044)
Asian	-0.214^{***}		-0.191^{***}	-0.174^{**}	-0.193^{***}
	(0.054)		(0.055)	(0.058)	(0.055)
Other	-0.096		-0.063	-0.059	-0.063
	(0.064)		(0.063)	(0.063)	(0.063)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.052	0.034	0.039	0.035	0.038
	(0.044)	(0.045)	(0.044)	(0.044)	(0.044)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.081	-0.093^{+}	-0.084^{+}	-0.085^{+}	-0.083^{+}
	(0.050)	(0.051)	(0.050)	(0.050)	(0.050)
5,001-10,000	-0.135^{*}	-0.162^{**}	-0.150^{**}	-0.154^{**}	-0.152^{**}
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)
10,001-20,000	-0.183^{**}	-0.214^{***}	-0.187^{**}	-0.187^{**}	-0.189^{**}
	(0.059)	(0.059)	(0.058)	(0.058)	(0.058)
More than 20,000	-0.217^{***}	-0.258^{***}	-0.234^{***}	-0.238^{***}	-0.234^{***}
	(0.064)	(0.064)	(0.063)	(0.063)	(0.063)
FGLI Status (Ref: Not first-gen, not low-		0.000	0.000	0.000	0.000

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
income)					
		(.)	(.)	(.)	(.)
Low-income only		-0.107*	-0.085+	-0.081+	-0.081+
		(0.044)	(0.044)	(0.044)	(0.044)
First-gen only		-0.050	-0.046	-0.041	-0.051
		(0.039)	(0.039)	(0.039)	(0.039)
First-gen, low-income		-0.119**	-0.058	-0.059	-0.061
		(0.037)	(0.038)	(0.038)	(0.040)
Gender: Female			-0.025	-0.024	-0.025
			(0.028)	(0.028)	(0.028)
Student SAT/100, mean-centered			-0.004	-0.005	-0.004
			(0.009)	(0.009)	(0.009)
Student SAT: Imputation flag			-0.340	-0.338	-0.338
			(0.292)	(0.291)	(0.292)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
C to B-			0.427+	0.437+	0.427+
			(0.239)	(0.239)	(0.239)
B- to B			0.524*	0.541*	0.524*
			(0.238)	(0.238)	(0.238)
B to A-			0.638**	0.654**	0.638**
			(0.236)	(0.236)	(0.236)
A- to A			0.797***	0.812***	0.797***
			(0.236)	(0.236)	(0.237)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				-0.065*	
				(0.030)	
Hispanic # Median SAT of college/100, mean-centered				-0.017	
				(0.028)	
Asian # Median SAT of college/100,				-0.041	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
mean-centered					
				(0.035)	
Other # Median SAT of college/100, mean-centered				-0.045	
				(0.043)	
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.012
					(0.031)
First-gen only # Median SAT of college/100, mean-centered					-0.031
					(0.031)
First-gen, low-income # Median SAT of college/100, mean-centered					-0.013
					(0.027)
Constant	0.172**	0.201***	-0.448+	-0.465+	-0.449+
	(0.058)	(0.060)	(0.242)	(0.242)	(0.242)
Observations	5,150	5,150	5,150	5,150	5,150
Number of Groups	584	584	584	584	584

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.2: Multilevel Regression Results from Models Estimating the Association between College Selectivity and Behavioral Engagement

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.078***	0.070***	0.073***	0.066***	0.062**
	(0.015)	(0.015)	(0.016)	(0.019)	(0.019)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	0.225***		0.255***	0.301***	0.261***
	(0.049)		(0.051)	(0.055)	(0.051)
Hispanic	0.162***		0.165***	0.164***	0.167***
	(0.044)		(0.045)	(0.045)	(0.045)
Asian	0.221***		0.222***	0.240***	0.221***
	(0.055)		(0.056)	(0.059)	(0.056)
Other	0.076		0.086	0.085	0.087
	(0.064)		(0.064)	(0.064)	(0.064)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.057	0.080	0.046	0.049	0.051
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.064	-0.049	-0.072	-0.074	-0.074
	(0.056)	(0.056)	(0.055)	(0.055)	(0.055)
5,001-10,000	-0.109+	-0.075	-0.117+	-0.118+	-0.114+
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
10,001-20,000	-0.160*	-0.119+	-0.160*	-0.167*	-0.158*
	(0.066)	(0.066)	(0.065)	(0.066)	(0.065)
More than 20,000	-0.133+	-0.083	-0.145*	-0.150*	-0.144*
	(0.072)	(0.071)	(0.071)	(0.071)	(0.071)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		0.073	0.034	0.029	0.027
		(0.044)	(0.045)	(0.045)	(0.045)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		0.045 (0.039)	0.030 (0.039)	0.026 (0.039)	0.025 (0.040)
First-gen, low-income		0.090* (0.037)	0.025 (0.039)	0.021 (0.039)	0.043 (0.041)
Gender: Female			0.124*** (0.029)	0.124*** (0.029)	0.124*** (0.029)
Student SAT/100, mean-centered			-0.005 (0.009)	-0.004 (0.009)	-0.005 (0.009)
Student SAT: Imputation flag			-0.474 (0.295)	-0.473 (0.295)	-0.479 (0.295)
HS GPA (Ref: C or below)			0.000 (.)	0.000 (.)	0.000 (.)
C to B-			0.275 (0.242)	0.262 (0.242)	0.266 (0.242)
B- to B			0.381 (0.241)	0.364 (0.241)	0.370 (0.241)
B to A-			0.401+ (0.239)	0.383 (0.239)	0.390 (0.239)
A- to A			0.498* (0.239)	0.481* (0.239)	0.487* (0.239)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000 (.)	
Black # Median SAT of college/100, mean-centered				0.059+ (0.032)	
Hispanic # Median SAT of college/100, mean-centered				-0.008 (0.029)	
Asian # Median SAT of college/100, mean-centered				-0.024 (0.036)	
Other # Median SAT of college/100, mean-centered				0.015	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
				(0.044)	
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					-0.000
					(0.031)
First-gen only # Median SAT of college/100, mean-centered					0.011
					(0.031)
First-gen, low-income # Median SAT of college/100, mean-centered					0.049^{+}
					(0.028)
Constant	0.029	0.013	-0.474^{+}	-0.452^{+}	-0.462^{+}
	(0.065)	(0.066)	(0.247)	(0.247)	(0.247)
Observations	5,150	5,150	5,150	5,150	5,150
Number of Groups	584	584	584	584	584

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.3: OLS Regression Results from Models Estimating the Association between College Selectivity and Above Average Affective Engagement

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.046***	0.044***	0.039***	0.050***	0.041***
	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	-0.060*		-0.029	-0.050	-0.029
	(0.028)		(0.029)	(0.032)	(0.030)
Hispanic	-0.095***		-0.078**	-0.079**	-0.078**
	(0.027)		(0.029)	(0.029)	(0.029)
Asian	-0.078*		-0.069+	-0.062+	-0.069+
	(0.034)		(0.035)	(0.037)	(0.035)
Other	-0.044		-0.027	-0.025	-0.027
	(0.035)		(0.035)	(0.036)	(0.035)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.008	-0.003	-0.000	-0.003	-0.001
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.042	-0.047	-0.042	-0.044	-0.042
	(0.029)	(0.030)	(0.029)	(0.030)	(0.029)
5,001-10,000	-0.070*	-0.084*	-0.074*	-0.076*	-0.075*
	(0.032)	(0.032)	(0.031)	(0.032)	(0.031)
10,001-20,000	-0.093*	-0.109**	-0.095**	-0.095**	-0.096**
	(0.036)	(0.035)	(0.036)	(0.036)	(0.036)
More than 20,000	-0.123***	-0.144***	-0.131***	-0.133***	-0.131***
	(0.037)	(0.036)	(0.036)	(0.036)	(0.036)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		-0.028	-0.022	-0.020	-0.021
		(0.026)	(0.028)	(0.028)	(0.028)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.046^{+} (0.024)	-0.046^{+} (0.023)	-0.043^{+} (0.024)	-0.050^{*} (0.023)
First-gen, low-income		-0.073^{**} (0.023)	-0.052^{*} (0.025)	-0.052^{*} (0.025)	-0.054^{*} (0.026)
Gender: Female			0.016 (0.017)	0.017 (0.017)	0.016 (0.017)
Student SAT/100, mean-centered			-0.012^{*} (0.006)	-0.012^{*} (0.006)	-0.012^{*} (0.006)
Student SAT: Imputation flag			-0.125 (0.245)	-0.115 (0.244)	-0.118 (0.247)
HS GPA (Ref: C or below)			0.000 (.)	0.000 (.)	0.000 (.)
C to B-			0.018 (0.159)	0.024 (0.157)	0.016 (0.161)
B- to B			0.048 (0.159)	0.057 (0.158)	0.046 (0.161)
B to A-			0.083 (0.157)	0.092 (0.155)	0.082 (0.159)
A- to A			0.170 (0.154)	0.179 (0.153)	0.169 (0.156)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000 (.)	
Black # Median SAT of college/100, mean-centered				-0.034^{+} (0.019)	
Hispanic # Median SAT of college/100, mean-centered				-0.019 (0.017)	
Asian # Median SAT of college/100, mean-centered				-0.018 (0.021)	
Other # Median SAT of college/100, mean-centered				-0.015	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race) (0.027)	(5) Interaction (FGLI)
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.013
					(0.017)
First-gen only # Median SAT of college/100, mean-centered					-0.019
					(0.018)
First-gen, low-income # Median SAT of college/100, mean-centered					-0.005
					(0.015)
Constant	0.650***	0.670***	0.558***	0.548***	0.559***
	(0.033)	(0.033)	(0.155)	(0.154)	(0.157)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.03	0.03	0.04	0.04	0.04

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.4: OLS Regression Results from Models Estimating the Association between College Selectivity and Above Average Behavioral Engagement

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.024**	0.021*	0.026**	0.028*	0.022*
	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	0.090**		0.101***	0.124***	0.106***
	(0.029)		(0.030)	(0.033)	(0.030)
Hispanic	0.071**		0.068**	0.063*	0.067**
	(0.022)		(0.024)	(0.025)	(0.024)
Asian	0.093*		0.093*	0.094*	0.093*
	(0.038)		(0.039)	(0.042)	(0.039)
Other	0.030		0.036	0.037	0.036
	(0.036)		(0.035)	(0.035)	(0.035)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.014	0.024	0.007	0.006	0.009
	(0.025)	(0.025)	(0.026)	(0.025)	(0.026)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.063+	-0.057	-0.065+	-0.065+	-0.066+
	(0.036)	(0.036)	(0.037)	(0.036)	(0.036)
5,001-10,000	-0.094*	-0.080*	-0.098*	-0.100**	-0.097**
	(0.037)	(0.037)	(0.038)	(0.038)	(0.037)
10,001-20,000	-0.114**	-0.098*	-0.115**	-0.122**	-0.117**
	(0.039)	(0.038)	(0.039)	(0.038)	(0.038)
More than 20,000	-0.106**	-0.086*	-0.112**	-0.117**	-0.112**
	(0.040)	(0.039)	(0.040)	(0.040)	(0.039)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		0.043	0.023	0.021	0.021
		(0.029)	(0.029)	(0.029)	(0.029)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		0.006	-0.004	-0.005	-0.014
		(0.024)	(0.024)	(0.024)	(0.024)
First-gen, low-income		0.039	0.006	0.005	0.019
		(0.025)	(0.028)	(0.028)	(0.031)
Gender identity: Female			0.046*	0.047*	0.047*
			(0.018)	(0.018)	(0.018)
Student SAT/100, mean-centered			-0.012*	-0.011*	-0.012*
			(0.005)	(0.005)	(0.006)
Student SAT: Imputation flag			0.142	0.148	0.149
			(0.262)	(0.264)	(0.263)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
HS GPA: C to B-			0.198^{+}	0.190^{+}	0.192^{+}
			(0.107)	(0.112)	(0.111)
B- to B			0.254*	0.244*	0.246*
			(0.115)	(0.120)	(0.120)
B to A-			0.265*	0.256*	0.258*
			(0.112)	(0.117)	(0.117)
A- to A			0.325**	0.316**	0.318**
			(0.115)	(0.120)	(0.120)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				0.021	
				(0.018)	
Hispanic # Median SAT of college/100, mean-centered				-0.028	
				(0.020)	
Asian # Median SAT of college/100, mean-centered				-0.003	
				(0.018)	
Other # Median SAT of college/100, mean-centered				-0.009	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race) (0.024)	(5) Interaction (FGLI)
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.012
					(0.019)
First-gen only # Median SAT of college/100, mean-centered					-0.024
					(0.021)
First-gen, low-income # Median SAT of college/100, mean-centered					0.025
					(0.019)
Constant	0.552***	0.547***	0.247*	0.260*	0.255*
	(0.038)	(0.039)	(0.115)	(0.120)	(0.119)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.01	0.01	0.02	0.02	0.02

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.5: OLS Regression Results from Models Estimating the Association between College Selectivity and Interactions with Faculty

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.034**	0.033**	0.009	0.014	-0.001
	(0.011)	(0.011)	(0.012)	(0.014)	(0.015)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	-0.113*		-0.047	-0.063	-0.041
	(0.052)		(0.055)	(0.059)	(0.055)
Hispanic	-0.084+		-0.048	-0.037	-0.047
	(0.043)		(0.047)	(0.047)	(0.047)
Asian	-0.172***		-0.161**	-0.133**	-0.159**
	(0.049)		(0.051)	(0.050)	(0.051)
Other	-0.125+		-0.096	-0.095	-0.095
	(0.073)		(0.072)	(0.073)	(0.072)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.156***	0.141***	0.141***	0.143***	0.144***
	(0.040)	(0.040)	(0.041)	(0.042)	(0.041)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.039	-0.044	-0.040	-0.042	-0.042
	(0.044)	(0.045)	(0.044)	(0.044)	(0.043)
5,001-10,000	-0.112*	-0.131*	-0.119*	-0.116*	-0.118*
	(0.052)	(0.051)	(0.051)	(0.052)	(0.051)
10,001-20,000	-0.172***	-0.194***	-0.174***	-0.170***	-0.176***
	(0.047)	(0.047)	(0.048)	(0.049)	(0.047)
More than 20,000	-0.227***	-0.256***	-0.242***	-0.242***	-0.245***
	(0.051)	(0.050)	(0.050)	(0.050)	(0.050)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		-0.050	-0.036	-0.036	-0.041
		(0.045)	(0.048)	(0.048)	(0.049)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.066	-0.061	-0.060	-0.065
		(0.041)	(0.041)	(0.041)	(0.043)
First-gen, low-income		-0.088*	-0.047	-0.050	-0.036
		(0.039)	(0.043)	(0.043)	(0.044)
Gender: Female			0.014	0.015	0.014
			(0.030)	(0.030)	(0.030)
Student SAT/100, mean-centered			0.005	0.004	0.005
			(0.010)	(0.010)	(0.010)
Student SAT: Imputation flag			-0.223	-0.232	-0.220
			(0.586)	(0.579)	(0.587)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
C to B-			0.136	0.141	0.128
			(0.331)	(0.334)	(0.329)
B- to B			0.135	0.143	0.124
			(0.331)	(0.335)	(0.331)
B to A-			0.272	0.277	0.261
			(0.328)	(0.331)	(0.327)
A- to A			0.380	0.386	0.369
			(0.326)	(0.330)	(0.325)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				-0.022	
				(0.034)	
Hispanic # Median SAT of college/100, mean-centered				0.032	
				(0.029)	
Asian # Median SAT of college/100, mean-centered				-0.054+	
				(0.033)	
Other # Median SAT of college/100, mean-centered				-0.021	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race) (0.042)	(5) Interaction (FGLI)
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.018
					(0.026)
First-gen only # Median SAT of college/100, mean-centered					0.013
					(0.037)
First-gen, low-income # Median SAT of college/100, mean-centered					0.034
					(0.026)
Constant	4.434***	4.455***	4.168***	4.159***	4.183***
	(0.045)	(0.043)	(0.330)	(0.333)	(0.329)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.04	0.04	0.05	0.05	0.05

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.6: OLS Regression Results from Models Estimating the Association between College Selectivity and Academic Satisfaction

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.052***	0.055***	0.015	0.019	-0.001
	(0.013)	(0.013)	(0.015)	(0.019)	(0.017)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	-0.250***		-0.146*	-0.180*	-0.141*
	(0.054)		(0.059)	(0.072)	(0.059)
Hispanic	-0.102+		-0.052	-0.041	-0.048
	(0.055)		(0.057)	(0.057)	(0.057)
Asian	-0.269***		-0.250***	-0.220**	-0.246***
	(0.063)		(0.066)	(0.069)	(0.066)
Other	-0.167*		-0.122+	-0.122+	-0.121+
	(0.073)		(0.073)	(0.073)	(0.073)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.031	0.009	0.014	0.015	0.013
	(0.042)	(0.042)	(0.044)	(0.044)	(0.044)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.029	-0.042	-0.036	-0.038	-0.039
	(0.056)	(0.056)	(0.055)	(0.055)	(0.056)
5,001-10,000	-0.067	-0.101	-0.080	-0.076	-0.082
	(0.060)	(0.062)	(0.060)	(0.060)	(0.060)
10,001-20,000	-0.129*	-0.164**	-0.133*	-0.125*	-0.136*
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
More than 20,000	-0.152*	-0.196**	-0.174**	-0.170**	-0.181**
	(0.061)	(0.061)	(0.061)	(0.061)	(0.062)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		-0.098+	-0.068	-0.067	-0.075
		(0.055)	(0.058)	(0.058)	(0.059)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.059	-0.050	-0.047	-0.049
		(0.048)	(0.048)	(0.048)	(0.049)
First-gen, low-income		-0.119**	-0.042	-0.045	-0.048
		(0.041)	(0.044)	(0.044)	(0.047)
Gender: Female			0.029	0.029	0.030
			(0.034)	(0.034)	(0.034)
Student SAT/100, mean-centered			0.010	0.009	0.010
			(0.011)	(0.011)	(0.011)
Student SAT: Imputation flag			-0.404	-0.411	-0.395
			(0.547)	(0.540)	(0.558)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
C to B-			0.198	0.209	0.184
			(0.378)	(0.385)	(0.381)
B- to B			0.377	0.394	0.364
			(0.382)	(0.389)	(0.385)
B to A-			0.482	0.495	0.466
			(0.382)	(0.389)	(0.385)
A- to A			0.642+	0.656+	0.628+
			(0.376)	(0.383)	(0.379)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				-0.039	
				(0.044)	
Hispanic # Median SAT of college/100, mean-centered				0.039	
				(0.033)	
Asian # Median SAT of college/100, mean-centered				-0.057	
				(0.045)	
Other # Median SAT of college/100, mean-centered				0.032	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race) (0.037)	(5) Interaction (FGLI)
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.050
					(0.031)
First-gen only # Median SAT of college/100, mean-centered					0.047
					(0.038)
First-gen, low-income # Median SAT of college/100, mean-centered					0.022
					(0.028)
Constant	4.301***	4.321***	3.805***	3.787***	3.830***
	(0.051)	(0.053)	(0.386)	(0.393)	(0.390)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.02	0.01	0.04	0.04	0.04

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.7: OLS Regression Results from Models Estimating the Association between College Selectivity and Interactions with Peers

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.066***	0.065***	0.052**	0.065***	0.059***
	(0.014)	(0.014)	(0.016)	(0.018)	(0.018)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	-0.000		0.042	-0.000	0.043
	(0.045)		(0.051)	(0.059)	(0.052)
Hispanic	-0.154**		-0.131*	-0.126*	-0.133**
	(0.047)		(0.050)	(0.050)	(0.051)
Asian	-0.012		-0.007	0.002	-0.009
	(0.061)		(0.063)	(0.066)	(0.062)
Other	-0.005		0.017	0.019	0.016
	(0.065)		(0.063)	(0.063)	(0.063)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.011	0.001	0.002	-0.000	0.003
	(0.046)	(0.046)	(0.047)	(0.047)	(0.046)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.013	-0.014	-0.011	-0.013	-0.010
	(0.044)	(0.045)	(0.044)	(0.045)	(0.044)
5,001-10,000	-0.048	-0.059	-0.052	-0.052	-0.051
	(0.052)	(0.053)	(0.053)	(0.054)	(0.053)
10,001-20,000	-0.107+	-0.124*	-0.107+	-0.103+	-0.108+
	(0.056)	(0.056)	(0.056)	(0.057)	(0.056)
More than 20,000	-0.112*	-0.134*	-0.122*	-0.121*	-0.118*
	(0.056)	(0.057)	(0.056)	(0.057)	(0.056)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		-0.054	-0.047	-0.043	-0.043
		(0.041)	(0.042)	(0.042)	(0.042)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.081^{+} (0.049)	-0.075 (0.049)	-0.070 (0.050)	-0.086^{+} (0.050)
First-gen, low-income		-0.050 (0.033)	-0.027 (0.036)	-0.027 (0.036)	-0.015 (0.037)
Gender: Female			-0.020 (0.030)	-0.020 (0.030)	-0.020 (0.030)
Student SAT/100, mean-centered			-0.007 (0.009)	-0.008 (0.009)	-0.007 (0.009)
Student SAT: Imputation flag			-0.485 (0.555)	-0.479 (0.566)	-0.480 (0.557)
HS GPA (Ref: C or below)			0.000 (.)	0.000 (.)	0.000 (.)
C to B-			0.376 (0.301)	0.388 (0.298)	0.378 (0.301)
B- to B			0.404 (0.300)	0.422 (0.297)	0.404 (0.300)
B to A-			0.481 (0.295)	0.499^{+} (0.293)	0.483 (0.295)
A- to A			0.588* (0.296)	0.605* (0.293)	0.590* (0.296)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000 (.)	
Black # Median SAT of college/100, mean-centered				-0.059^{+} (0.035)	
Hispanic # Median SAT of college/100, mean-centered				0.001 (0.029)	
Asian # Median SAT of college/100, mean-centered				-0.027 (0.037)	
Other # Median SAT of college/100, mean-centered				-0.034	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
				(0.039)	
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					-0.009
					(0.022)
First-gen only # Median SAT of college/100, mean-centered					-0.058^{+}
					(0.033)
First-gen, low-income # Median SAT of college/100, mean-centered					0.003
					(0.026)
Constant	4.467***	4.496***	4.001***	3.981***	3.994***
	(0.056)	(0.055)	(0.293)	(0.291)	(0.293)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.02	0.02	0.03	0.03	0.03

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.8: OLS Regression Results from Models Estimating the Association between College Selectivity and Social Satisfaction

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.070***	0.064***	0.060**	0.090***	0.074**
	(0.018)	(0.019)	(0.022)	(0.024)	(0.024)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	-0.061		-0.001	-0.076	-0.005
	(0.064)		(0.069)	(0.074)	(0.068)
Hispanic	-0.226***		-0.190**	-0.195**	-0.193**
	(0.066)		(0.070)	(0.069)	(0.070)
Asian	-0.124+		-0.104	-0.104	-0.107
	(0.075)		(0.078)	(0.080)	(0.078)
Other	-0.103		-0.069	-0.064	-0.070
	(0.082)		(0.082)	(0.082)	(0.081)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	-0.025	-0.042	-0.035	-0.043	-0.037
	(0.055)	(0.056)	(0.055)	(0.055)	(0.056)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.041	-0.045	-0.042	-0.044	-0.040
	(0.070)	(0.071)	(0.071)	(0.072)	(0.071)
5,001-10,000	-0.169*	-0.193**	-0.176*	-0.181*	-0.179*
	(0.073)	(0.073)	(0.073)	(0.076)	(0.074)
10,001-20,000	-0.099	-0.130+	-0.103	-0.102	-0.105
	(0.074)	(0.075)	(0.075)	(0.076)	(0.075)
More than 20,000	-0.152+	-0.193*	-0.168*	-0.170*	-0.163*
	(0.078)	(0.079)	(0.079)	(0.080)	(0.079)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		-0.117*	-0.103+	-0.096+	-0.095+
		(0.052)	(0.056)	(0.055)	(0.056)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.101^{+} (0.052)	-0.098^{+} (0.051)	-0.087^{+} (0.051)	-0.112* (0.050)
First-gen, low-income		-0.141** (0.047)	-0.106* (0.051)	-0.104* (0.051)	-0.108^{+} (0.055)
Gender: Female			0.018 (0.041)	0.018 (0.041)	0.018 (0.041)
Student SAT/100, mean-centered			-0.024^{+} (0.013)	-0.026* (0.013)	-0.025^{+} (0.013)
Student SAT: Imputation flag			-0.852 (0.982)	-0.820 (0.986)	-0.836 (0.993)
HS GPA (Ref: C or below)			0.000 (.)	0.000 (.)	0.000 (.)
C to B-			0.356 (0.437)	0.377 (0.433)	0.359 (0.442)
B- to B			0.448 (0.440)	0.479 (0.436)	0.450 (0.444)
B to A-			0.489 (0.433)	0.523 (0.430)	0.496 (0.438)
A- to A			0.628 (0.435)	0.659 (0.432)	0.633 (0.439)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000 (.)	
Black # Median SAT of college/100, mean-centered				-0.110* (0.048)	
Hispanic # Median SAT of college/100, mean-centered				-0.058^{+} (0.034)	
Asian # Median SAT of college/100, mean-centered				-0.021 (0.050)	
Other # Median SAT of college/100, mean-centered				-0.046	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
				(0.051)	
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.011
					(0.035)
First-gen only # Median SAT of college/100, mean-centered					-0.086*
					(0.035)
First-gen, low-income # Median SAT of college/100, mean-centered					-0.029
					(0.039)
Constant	4.210***	4.257***	3.728***	3.694***	3.717***
	(0.073)	(0.073)	(0.435)	(0.432)	(0.440)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.01	0.01	0.02	0.02	0.02

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.9: OLS Regression Results from Models Estimating the Association between College Selectivity and Belonging

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.114***	0.111***	0.102***	0.119***	0.118***
	(0.014)	(0.014)	(0.018)	(0.021)	(0.019)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	-0.055		-0.002	-0.086	-0.007
	(0.059)		(0.063)	(0.076)	(0.063)
Hispanic	-0.192***		-0.164**	-0.163**	-0.167**
	(0.054)		(0.056)	(0.055)	(0.057)
Asian	-0.113+		-0.103	-0.105	-0.107
	(0.066)		(0.068)	(0.070)	(0.069)
Other	-0.063		-0.037	-0.036	-0.038
	(0.077)		(0.077)	(0.078)	(0.077)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	-0.009	-0.026	-0.020	-0.024	-0.021
	(0.053)	(0.053)	(0.054)	(0.054)	(0.054)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.092	-0.096	-0.092	-0.093	-0.089
	(0.068)	(0.069)	(0.067)	(0.068)	(0.068)
5,001-10,000	-0.106	-0.127+	-0.112+	-0.112+	-0.113+
	(0.065)	(0.065)	(0.064)	(0.065)	(0.064)
10,001-20,000	-0.196**	-0.225***	-0.199**	-0.191**	-0.200**
	(0.065)	(0.065)	(0.065)	(0.067)	(0.066)
More than 20,000	-0.230***	-0.266***	-0.244***	-0.239***	-0.237***
	(0.068)	(0.068)	(0.069)	(0.070)	(0.070)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		-0.093+	-0.080	-0.073	-0.072
		(0.049)	(0.052)	(0.051)	(0.053)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.100*	-0.096*	-0.088+	-0.107*
		(0.046)	(0.046)	(0.045)	(0.045)
First-gen, low-income		-0.097*	-0.060	-0.059	-0.059
		(0.042)	(0.044)	(0.044)	(0.048)
Gender: Female			0.001	0.001	0.001
			(0.040)	(0.040)	(0.040)
Student SAT/100, mean-centered			-0.017	-0.019	-0.017
			(0.012)	(0.012)	(0.012)
Student SAT: Imputation flag			-0.436	-0.417	-0.427
			(0.796)	(0.806)	(0.803)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
C to B-			0.447	0.471	0.454
			(0.451)	(0.450)	(0.453)
B- to B			0.481	0.516	0.488
			(0.455)	(0.454)	(0.457)
B to A-			0.589	0.625	0.599
			(0.452)	(0.453)	(0.454)
A- to A			0.699	0.732	0.707
			(0.449)	(0.449)	(0.451)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				-0.104*	
				(0.048)	
Hispanic # Median SAT of college/100, mean-centered				-0.010	
				(0.029)	
Asian # Median SAT of college/100, mean-centered				-0.012	
				(0.038)	
Other # Median SAT of college/100, mean-centered				0.008	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
				(0.043)	
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					-0.011
					(0.029)
First-gen only # Median SAT of college/100, mean-centered					-0.081*
					(0.036)
First-gen, low-income # Median SAT of college/100, mean-centered					-0.026
					(0.035)
Constant	4.397***	4.436***	3.833***	3.793***	3.816***
	(0.066)	(0.066)	(0.453)	(0.452)	(0.455)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.03	0.03	0.04	0.04	0.04

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.10: OLS Regression Results from Models Estimating the Association between College Selectivity and Use of Academic Advising Services

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.010^{+}	0.011^{+}	0.000	-0.001	-0.002
	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	-0.049^{+}		-0.020	-0.016	-0.019
	(0.027)		(0.028)	(0.031)	(0.028)
Hispanic	-0.015		-0.006	-0.006	-0.005
	(0.021)		(0.023)	(0.022)	(0.023)
Asian	-0.059*		-0.054^{+}	-0.052^{+}	-0.054^{+}
	(0.029)		(0.029)	(0.029)	(0.029)
Other	-0.014		-0.005	-0.005	-0.005
	(0.028)		(0.028)	(0.028)	(0.028)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.019	0.013	0.010	0.010	0.010
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	0.019	0.016	0.014	0.014	0.013
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
5,001-10,000	-0.017	-0.023	-0.021	-0.021	-0.022
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
10,001-20,000	-0.012	-0.019	-0.015	-0.015	-0.016
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
More than 20,000	0.009	-0.001	-0.000	-0.000	-0.001
	(0.027)	(0.028)	(0.027)	(0.027)	(0.027)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		0.004	0.009	0.009	0.008
		(0.019)	(0.020)	(0.020)	(0.020)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.017	-0.016	-0.017	-0.019
		(0.018)	(0.019)	(0.019)	(0.019)
First-gen, low-income		-0.020	-0.005	-0.005	-0.003
		(0.020)	(0.020)	(0.020)	(0.020)
Gender: Female			0.049***	0.049***	0.049***
			(0.014)	(0.014)	(0.014)
Student SAT/100, mean-centered			0.007	0.007	0.008
			(0.006)	(0.006)	(0.006)
Student SAT: Imputation flag			-0.021	-0.022	-0.017
			(0.208)	(0.208)	(0.209)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
C to B-			-0.077	-0.078	-0.081
			(0.134)	(0.135)	(0.134)
B- to B			-0.013	-0.014	-0.017
			(0.132)	(0.133)	(0.133)
B to A-			0.024	0.022	0.020
			(0.131)	(0.132)	(0.132)
A- to A			0.043	0.042	0.039
			(0.131)	(0.132)	(0.132)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				0.006	
				(0.017)	
Hispanic # Median SAT of college/100, mean-centered				0.001	
				(0.013)	
Asian # Median SAT of college/100, mean-centered				-0.002	
				(0.017)	
Other # Median SAT of college/100, mean-centered				0.014	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race) (0.017)	(5) Interaction (FGLI)
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.014
					(0.012)
First-gen only # Median SAT of college/100, mean-centered					-0.004
					(0.016)
First-gen, low-income # Median SAT of college/100, mean-centered					0.006
					(0.015)
Constant	0.830***	0.833***	0.790***	0.792***	0.795***
	(0.024)	(0.026)	(0.135)	(0.137)	(0.136)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.01	0.01	0.02	0.02	0.02

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.11: OLS Regression Results from Models Estimating the Association between College Selectivity and Use of Academic Support Services

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.017^{+}	0.014	0.031**	0.035**	0.026*
	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	0.100***		0.093**	0.118***	0.099***
	(0.029)		(0.029)	(0.034)	(0.029)
Hispanic	0.083***		0.069**	0.065**	0.068**
	(0.023)		(0.025)	(0.025)	(0.025)
Asian	0.108**		0.104**	0.118**	0.105**
	(0.034)		(0.035)	(0.039)	(0.035)
Other	0.054		0.053	0.054	0.053
	(0.037)		(0.036)	(0.036)	(0.036)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.003	0.015	-0.001	-0.001	0.003
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.053	-0.046	-0.054	-0.055	-0.056
	(0.037)	(0.036)	(0.037)	(0.036)	(0.036)
5,001-10,000	-0.098*	-0.081*	-0.100**	-0.102**	-0.098**
	(0.038)	(0.037)	(0.037)	(0.037)	(0.037)
10,001-20,000	-0.095*	-0.076^{+}	-0.097*	-0.103*	-0.097*
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
More than 20,000	-0.110*	-0.086*	-0.113**	-0.120**	-0.113**
	(0.043)	(0.042)	(0.044)	(0.044)	(0.043)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		0.021	-0.004	-0.006	-0.006
		(0.028)	(0.027)	(0.027)	(0.028)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		0.013	-0.002	-0.003	-0.009
		(0.024)	(0.024)	(0.024)	(0.024)
First-gen, low-income		0.050*	0.005	0.003	0.023
		(0.025)	(0.027)	(0.027)	(0.029)
Gender: Female			0.059**	0.060**	0.060**
			(0.018)	(0.018)	(0.018)
Student SAT/100, mean-centered			-0.024***	-0.023***	-0.024***
			(0.006)	(0.006)	(0.006)
Student SAT: Imputation flag			0.244	0.250	0.243
			(0.227)	(0.229)	(0.226)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
C to B-			0.179	0.171	0.175
			(0.110)	(0.114)	(0.114)
B- to B			0.228+	0.218+	0.222+
			(0.117)	(0.121)	(0.121)
B to A-			0.223+	0.212+	0.216+
			(0.114)	(0.118)	(0.119)
A- to A			0.257*	0.248*	0.251*
			(0.118)	(0.122)	(0.122)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				0.020	
				(0.018)	
Hispanic # Median SAT of college/100, mean-centered				-0.028	
				(0.020)	
Asian # Median SAT of college/100, mean-centered				-0.025	
				(0.024)	
Other # Median SAT of college/100, mean-centered				0.000	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race) (0.026)	(5) Interaction (FGLI)
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					-0.006
					(0.017)
First-gen only # Median SAT of college/100, mean-centered					-0.010
					(0.021)
First-gen, low-income # Median SAT of college/100, mean-centered					0.035^{+}
					(0.019)
Constant	0.516***	0.511***	0.256*	0.269*	0.262*
	(0.039)	(0.039)	(0.119)	(0.122)	(0.123)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.01	0.01	0.02	0.03	0.03

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.12: OLS Regression Results from Models Estimating the Association between College Selectivity and Use of Career Services

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
Median SAT of college/100, mean-centered	0.029***	0.026***	0.024***	0.019*	0.024**
	(0.006)	(0.006)	(0.007)	(0.009)	(0.008)
Racial/ethnic identity (Ref: White)	0.000		0.000	0.000	0.000
	(.)		(.)	(.)	(.)
Black	0.076**		0.086***	0.104***	0.086***
	(0.024)		(0.024)	(0.029)	(0.023)
Hispanic	0.019		0.024	0.020	0.024
	(0.018)		(0.018)	(0.019)	(0.018)
Asian	0.079**		0.079**	0.065*	0.079**
	(0.028)		(0.029)	(0.031)	(0.029)
Other	0.005		0.009	0.009	0.009
	(0.027)		(0.026)	(0.027)	(0.027)
Control of first college (Ref: Public)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Private	0.041+	0.046*	0.037	0.037	0.036
	(0.022)	(0.022)	(0.022)	(0.023)	(0.023)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2,501-5,000	-0.014	-0.010	-0.015	-0.014	-0.015
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
5,001-10,000	0.014	0.024	0.014	0.013	0.013
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
10,001-20,000	-0.034	-0.025	-0.035	-0.037	-0.036
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
More than 20,000	-0.002	0.009	-0.006	-0.007	-0.007
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)
Low-income only		0.055*	0.046+	0.045+	0.046+
		(0.025)	(0.025)	(0.025)	(0.025)

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race)	(5) Interaction (FGLI)
First-gen only		-0.006	-0.008	-0.010	-0.010
		(0.017)	(0.017)	(0.017)	(0.017)
First-gen, low-income		0.015	-0.002	-0.000	-0.003
		(0.018)	(0.019)	(0.019)	(0.021)
Gender: Female			0.003	0.003	0.004
			(0.015)	(0.015)	(0.015)
Student SAT/100, mean-centered			0.001	0.001	0.001
			(0.004)	(0.004)	(0.004)
Student SAT: Imputation flag			-0.203***	-0.204***	-0.199***
			(0.030)	(0.030)	(0.031)
HS GPA (Ref: C or below)			0.000	0.000	0.000
			(.)	(.)	(.)
C to B-			0.127**	0.121*	0.125**
			(0.047)	(0.047)	(0.047)
B- to B			0.144**	0.136**	0.142**
			(0.043)	(0.044)	(0.043)
B to A-			0.152***	0.145***	0.150***
			(0.041)	(0.041)	(0.041)
A- to A			0.187***	0.180***	0.185***
			(0.043)	(0.043)	(0.043)
Racial/ethnic identity (Ref: White) # Median SAT of college/100, mean-centered				0.000	
				(.)	
Black # Median SAT of college/100, mean-centered				0.024	
				(0.016)	
Hispanic # Median SAT of college/100, mean-centered				-0.009	
				(0.013)	
Asian # Median SAT of college/100, mean-centered				0.029	
				(0.019)	
Other # Median SAT of college/100, mean-centered				-0.003	

	(1) Baseline (Race)	(2) Baseline (FGLI)	(3) Full	(4) Interaction (Race) (0.021)	(5) Interaction (FGLI)
FGLI Status (Ref: Not first-gen, not low-income) # Median SAT of college/100, mean-centered					0.000
					(.)
Low-income only # Median SAT of college/100, mean-centered					0.010
					(0.017)
First-gen only # Median SAT of college/100, mean-centered					-0.008
					(0.012)
First-gen, low-income # Median SAT of college/100, mean-centered					-0.001
					(0.014)
Constant	0.173***	0.171***	0.008	0.017	0.010
	(0.029)	(0.030)	(0.050)	(0.050)	(0.050)
N(Unweighted)	5,150	5,150	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660	1,226,660	1,226,660
R-squared	0.02	0.02	0.02	0.03	0.03

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.13: OLS Regression Results from Models Estimating the Association between Percent Black and Affective Engagement

	(1) Baseline (Race)	(2) Full	(3) Interaction (Race)
Percent of Black-identifying students	-0.001	-0.000	-0.005^{+}
	(0.001)	(0.001)	(0.003)
Racial/ethnic identity (Ref: White)	0.000	0.000	0.000
	(.)	(.)	(.)
Black	-0.192**	-0.060	-0.147^{+}
	(0.065)	(0.067)	(0.082)
Hispanic	-0.245***	-0.161**	-0.158^{+}
	(0.055)	(0.059)	(0.087)
Asian	-0.180**	-0.157*	-0.247*
	(0.068)	(0.070)	(0.106)
Other	-0.133^{+}	-0.079	-0.118
	(0.074)	(0.071)	(0.086)
Control of first college (Ref: Public)	0.000	0.000	0.000
	(.)	(.)	(.)
Private	0.201***	0.113**	0.111**
	(0.040)	(0.041)	(0.041)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000
	(.)	(.)	(.)
2,501-5,000	-0.040	-0.051	-0.053
	(0.059)	(0.057)	(0.057)
5,001-10,000	-0.042	-0.096	-0.090
	(0.062)	(0.059)	(0.059)
10,001-20,000	-0.057	-0.119^{+}	-0.110^{+}
	(0.062)	(0.061)	(0.061)
More than 20,000	-0.041	-0.149*	-0.146*
	(0.060)	(0.058)	(0.058)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000
		(.)	(.)
Low-income only		-0.103^{+}	-0.102^{+}
		(0.054)	(0.054)
First-gen only		-0.119*	-0.117*
		(0.049)	(0.049)
First-gen, low-income		-0.104*	-0.104*
		(0.042)	(0.043)

	(1) Baseline (Race)	(2) Full	(3) Interaction (Race)
Gender: Female		0.009	0.010
		(0.036)	(0.036)
Student SAT/100, mean-centered		0.005	0.004
		(0.010)	(0.010)
Student SAT: Imputation flag		-0.641	-0.635
		(0.687)	(0.694)
HS GPA (Ref: C or below)		0.000	0.000
		(.)	(.)
C to B-		0.430	0.442
		(0.376)	(0.379)
B- to B		0.526	0.543
		(0.379)	(0.381)
B to A-		0.660^{+}	0.672^{+}
		(0.373)	(0.376)
A- to A		0.837*	0.852*
		(0.370)	(0.373)
Racial/ethnic identity (Ref: White) # Percent of Black-identifying students			0.000
			(.)
Black # Percent of Black-identifying students			0.007^{+}
			(0.003)
Hispanic # Percent of Black-identifying students			-0.000
			(0.011)
Asian # Percent of Black-identifying students			0.012
			(0.010)
Other # Percent of Black-identifying students			0.005
			(0.006)
Constant	0.036	-0.540	-0.522
	(0.058)	(0.374)	(0.375)
N(Unweighted)	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660
R-squared	0.02	0.05	0.05

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).

Table A3.14: OLS Regression Results from Models Estimating the Association between Percent White and Affective Engagement

	(1) Baseline (Race)	(2) Full	(3) Interaction (Race)
Percent of White-identifying students	0.002^{+}	0.001	0.005***
	(0.001)	(0.001)	(0.001)
Racial/ethnic identity (Ref: White)	0.000	0.000	0.000
	(.)	(.)	(.)
Black	-0.168**	-0.029	0.406**
	(0.060)	(0.064)	(0.133)
Hispanic	-0.211***	-0.133*	0.172
	(0.059)	(0.064)	(0.150)
Asian	-0.152*	-0.132^{+}	-0.079
	(0.069)	(0.070)	(0.247)
Other	-0.117	-0.065	0.238
	(0.076)	(0.073)	(0.199)
Control of first college (Ref: Public)	0.000	0.000	0.000
	(.)	(.)	(.)
Private	0.213***	0.121**	0.144***
	(0.039)	(0.040)	(0.041)
College enrollment (Ref: 0-2,500)	0.000	0.000	0.000
	(.)	(.)	(.)
2,501-5,000	-0.035	-0.046	-0.048
	(0.059)	(0.057)	(0.056)
5,001-10,000	-0.027	-0.083	-0.070
	(0.063)	(0.059)	(0.060)
10,001-20,000	-0.042	-0.108^{+}	-0.079
	(0.064)	(0.062)	(0.062)
More than 20,000	-0.018	-0.133*	-0.090
	(0.062)	(0.060)	(0.060)
FGLI Status (Ref: Not first-gen, not low-income)		0.000	0.000
		(.)	(.)
Low-income only		-0.101^{+}	-0.105^{+}
		(0.054)	(0.054)
First-gen only		-0.121*	-0.119*
		(0.049)	(0.048)
First-gen, low-income		-0.101*	-0.103*
		(0.042)	(0.043)

	(1) Baseline (Race)	(2) Full	(3) Interaction (Race)
Gender: Female		0.010	0.010
		(0.036)	(0.036)
Student SAT/100, mean-centered		0.005	0.008
		(0.010)	(0.009)
Student SAT: Imputation flag		-0.670	-0.628
		(0.698)	(0.690)
HS GPA (Ref: C or below)		0.000	0.000
		(.)	(.)
C to B-		0.435	0.457
		(0.376)	(0.378)
B- to B		0.529	0.552
		(0.378)	(0.379)
B to A-		0.662^{+}	0.688^{+}
		(0.373)	(0.374)
A- to A		0.839^{*}	0.862^{*}
		(0.370)	(0.371)
Racial/ethnic identity (Ref: White) # Percent of White-identifying students			0.000
			(.)
Black # Percent of White-identifying students			-0.008^{***}
			(0.002)
Hispanic # Percent of White-identifying students			-0.005^{*}
			(0.003)
Asian # Percent of White-identifying students			0.000
			(0.004)
Other # Percent of White-identifying students			-0.005
			(0.003)
Constant	-0.100	-0.655^{+}	-0.933^{*}
	(0.097)	(0.372)	(0.370)
N(Unweighted)	5,150	5,150	5,150
N(Weighted)	1,226,660	1,226,660	1,226,660
R-squared	0.02	0.05	0.05

+ p<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Source. U.S. Department of Education, National Center for Education Statistics, 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17).