A Sociological Analysis of Structural Racism in Student List Products

ABSTRACT

Colleges identify prospective students by purchasing "student lists." Student list products are algorithmic selection devices that use search filters (e.g., test score, zip code) to select prospective students. We ask, what is the relationship between search filters and the racial composition of included versus excluded students? Drawing from the sociology of race, we conceptualize certain search filters as structurally racist inputs. Structurally racist inputs are determinants of selection devices that are correlated with race because some groups have been historically excluded from the input. We test propositions using a nationally representative sample of high school students. Several academic and geographic filters systematically exclude Black and Hispanic students. We motivate critical policy research on third-party products and vendors in education.

1 Introduction

Racial inequality in college access remains an enduring barrier to social mobility. Despite absolute increases in the number of Black and Hispanic students enrolling in college over the last few decades, a greater overall share of White and Asian students than Black and Hispanic students still enroll in college every year (Baker, Klasik, & Reardon, 2018). Based on the High School Longitudinal Survey of 2009, about 83% of Asian, 72% of White, 63% of Hispanic, and 62% of Black students enrolled in college within a year and a half of graduating high school in 2013 (Reber & Smith, 2023). For students that matriculate into college, college selectivity is a strong predictor of outcomes such as degree completion (Shamsuddin, 2016), initial job market participation (M. C. Long, 2008), earnings growth over time (MacLeod, Riehl, Saavedra, & Urquiola, 2017), and ability to repay student loans (Jackson & Reynolds, 2013). However, Black and Hispanic students are also substantially less likely to attend selective colleges than White and Asian students (Alon & Tienda, 2007; Posselt, Jaquette, Bielby, & Bastedo, 2012). Moreover, the disproportionate impact of COVID19 on Black and Hispanic students is estimated to have worsened racial disparities in whether and where students enroll in college (Ahn & Dominguez-Villegas, 2022).

Economics models the market for college access "as a two-sided matching problem in which the efficient outcome allocates students to colleges based on students' ability to benefit from the type and magnitude of the human capital investment that the college offers" (Hoxby, 2009, p. 106). Hoxby (2009) argues that information costs were the primary barrier to efficient matches. Students want to attend the best possible college but they don't know where they will be admitted and how much it will cost. Colleges want to enroll the best possible students, but they don't know who or where the "good" students are. Hoxby (2009, p. 103) notes that "In 1955, there was *no* early national college aptitude test. Students and colleges simply did not know where students stood in the national distribution of high school graduates' achievement or aptitude." Colleges could not make an apples-to-apples comparison between students from different schools because the information on a high school transcript "is relative to a standard that a college will not understand unless it draws very often from the high school" (Hoxby, 2009, p. 103).

Whereas sociology often conceives of standardized tests as mechanisms that amplify historic structural inequality (e.g., Alon & Tienda, 2007; Tiako, South, & Ray, 2021), Hoxby (2009) credits the standardized college entrance exam for creating an efficient, national higher education market by causing a "dramatic fall" (p. 102) in the cost of "colleges' information about students." From 1955 to 1990 the number of colleges requiring the SAT/ACT increased dramatically from 143 to 1,839, while the number of SAT/ACT test-takers per freshman seat increased from 0.23 in 1955 to 0.87 in 2005 (Hoxby, 2009). Test-takers can send scores to colleges they are interested in, allowing colleges to compare prospective students or prospects from disparate places. Following the creation of Title IV federal financial aid programs, US higher education finance can be conceived as a national voucher system, whereby tuition revenue – including household savings and financial aid – follows students to whichever institution they enroll in. Most colleges cannot survive solely from inquiries by prospects who reach out on their own (Ruffalo Noel-Levitz, 2022b). They must find desirable prospects who can be convinced to apply and enroll. In 1972 the College Board began selling lists of prospective students to colleges (Belkin, 2019), enabling colleges to identify and target desirable students across the country.

Student lists are a match-making intermediary connecting colleges to prospective students. A student list contains the contact information of prospective students who meet the search filter criteria (e.g., test score, GPA) specified by the university. Student lists are the fundamental input for undergraduate recruiting campaigns because purchased names – alongside "inquiries" who reach out on their own – constitute the set of prospects who receive subsequent recruiting interventions (e.g., mail, email) designed to push them towards the application and enrollment stages of the "enrollment funnel". Ruffalo Noel-Levitz (2022b, p. 5) reports that 86% of public universities "purchase high school student names to generate inquiries and applicants." Of these, 80% purchase more than 50,000 names annually. Howell, Hurwitz, Mabel, & Smith (2021) show that after controlling for covariates, 41.1% of students who participated in College Board Search – allowing accredited institutions to purchase their contact information — attended a 4-year college compared to 32.8% of students who opted out. Smith, Howell, & Hurwitz (2022) find that when a prospect's contact information is purchased by a college, they are more likely to enroll at the college.

Prior research has not investigated how the architecture of student list products makes certain prospects more or less likely to be targeted by colleges. We argue that student list products incorporate societal structural inequality in ways that exacerbate racial inequality in college access. Drawing from the sociology of race, we argue that the architecture of student list products reproduce structural inequality in two ways. First, the College Board and ACT student list products have historically excluded non test-takers, but rates of test-taking differ by race (Blake & Langenkamp, 2022). Second, colleges control which prospect profiles they purchase by filtering on "search filters" (e.g., AP score, zip code). We conceptualize several student list search filters as "racialized inputs" (Norris, 2021) that disadvantage underrepresented students of color because they have been historically excluded from this input. In turn, administrators utilizing student list products may disproportionately exclude communities of color because of college admissions criteria or because they have incomplete knowledge about how search filters interact with local patterns of exclusion.

This manuscript focuses on search filters from the College Board Student Search Service that we conceptualize as racialized inputs (Norris, 2021). We address three research questions. First, What is the relationship between individual search filters and the racial composition of included vs excluded students? Second, in what ways do public universities utilize racialized input search filters in concert with other search filters when purchasing student lists? Third, what is the racial composition of student list purchases that utilize racialized input search filters in concert with other search filters?

We address RQ1 by reconstructing the College Board Student Search Service product using a nationally representative sample of 9th graders in 2009 from the High School Longitudinal Survey (HSLS:09). Analyses simulate and compare the racial composition of included versus excluded prospects when individual search filters are utilized, focusing on test score (e.g., SAT, AP) and geography (e.g., zip code). We address RQ2 analyzing 830 student lists purchased by 14 public universities, which were collected via public records requests. We address RQ3 by showing the racial composition of selected student list purchases – simulated purchases based on HSLS data and actual purchases based on public records requests – that filter on multiple search filters simultaneously.

The manuscript is organized as follows. First, we provide background information about recruiting and student lists vis-a-vis scholarship on recruiting. Second, drawing from the sociology of race, we develop a conceptual framework about the architecture of student list products and how these products are utilized. Next, we describe methods and present results. Simulating purchases using HSLS:09, we find that search filters conceptualized as racialized inputs – filtering on taking a college entrance exam, test-score thresholds, or zip code affluence – are associated with racial inequality in targeted prospects. Additional simulations show that filtering on multiple racialized inputs may have a compounding effect on racial inequality. Finally, targeted analyses of lists purchased by public universities reveal extreme structural inequality, even in purchases that explicitly target underrepresented groups.

The manuscript concludes by discussing implications for policy and scholarship. Although some colleges may use student list products to increase access for underrepresented groups, the potential for unintended inequities seems high. The question becomes, should policymakers tolerate a product that is likely to do harm on the grounds that it is capable of doing good? As The US Department of Education (2023a) considers new federal regulations for "third-party servicers", we observe striking similarities between consumer report products, which are federally regulated, and student list products, which are not. Like consumer reports, student lists systematically lead to the extension of credit vis-a-vis student loans. With respect to state policy, we argue that state longitudinal data systems can create a more equitable alternative to private, third-party student lists. State-provided lists could serve an important function in direct admissions policies being adopted by several states (Odle & Delaney, 2022). We close by discussing future analyses of student list products and also broader scholarship about the role of third-party products and vendors in college access.

2 Background and Literature Review

2.1 Enrollment Management and the Enrollment Funnel

Enrollment management is the organizational behavior side of college access. The term enrollment management can refer to a profession, an administrative structure, or an industry. As a profession, enrollment management integrates techniques from marketing and economics in order to "influence the characteristics and the size of enrolled student bodies" (Hossler &

Bean, 1990, p. xiv). Beyond the basic goal of survival, colleges pursue some combination of broad enrollment goals (e.g., tuition revenue, academic profile, racial diversity) (Cheslock & Kroc, 2012; Hoxby, 2009; Winston, 1999), while also tending to specific needs of campus constituencies (e.g., College of Engineering needs majors, athletic teams need players) (Stevens, 2007). As an administrative structure, the office of enrollment management typically controls the activities of admissions, financial aid, and marketing and recruiting (Kraatz, Ventresca, & Deng, 2010). The enrollment management industry consists of university professionals (e.g., admissions counselors, VP for enrollment management), professional associations (e.g., National Association for College Admission Counseling), and third-party vendors/consultancies that interact with colleges and students (e.g., College Board, EAB, PowerSchool).

Colleges cannot realize their enrollment goals solely from prospects who find the college on their own. They must incite demand and discover desirable prospects who can be convinced to enroll. The "enrollment funnel" – depicted in Figure 1 – is a conceptual model used by enrollment management industry to depict broad stages in the process of recruiting students (American Association of Collegiate Registrars and Admissions Officers, 2018; EAB, 2019). The funnel begins with a large pool of "prospects" (i.e., prospective students) that the university would like to enroll. "Leads" are prospects whose contact information has been obtained. "Inquiries" are prospects that contact your institution and consist of two types: first, inquiries who respond to an initial solicitation (e.g., email) from the university; and second, "student-as-first-contact" inquiries who reach out to the university on their own (e.g., sending ACT scores). Applicants consist of inquiries who apply plus "stealth applicants" who do not contact the university before applying. The funnel narrows at each successive stage in order to convey the assumption of "melt" at each stage (e.g., a subset of "inquiries" will apply).

Practically, the purpose of the enrollment funnel is to inform recruiting interventions that target one or more stage. These interventions seek to increase the probability of "conversion" across stages (Campbell, 2017). At the top of the enrollment funnel, purchasing student lists is the primary means of converting prospects to leads. Purchased leads are served emails, brochures, and targeted social media advertisements designed to solicit inquiries and applications (Ruffalo Noel-Levitz, 2022b). Digital (e.g., Google display ads, YouTube) and traditional (e.g., TV, billboards) advertising are means of raising brand awareness and soliciting student-as-first-contact inquiries and (Cellini & Chaudhary, forthcoming; Ruffalo Noel-Levitz, 2022b). At the bottom of the funnel, colleges offer financial aid packages to convert admits to enrolled students (e.g., Hurwitz, 2012).

2.2 Scholarship on Recruiting

Scholarship on enrollment management behaviors targeting college access tend to focus on the latter stages of the enrollment funnel, particularly the process of deciding which applicants to admit (Bastedo, Howard, & Flaster, 2016; Killgore, 2009; e.g., Posselt, 2016) and the use of financial aid to convert admits to enrolled students (Doyle, 2010; Leeds & DesJardins, 2015; McPherson & Schapiro, 1998). Fewer studies investigate the earlier "recruiting" stages of identifying prospects, acquiring leads, and soliciting inquiries and applications.

Scholarship on recruiting from economics tends to estimate the effect of specific interventions on college access outcomes. Hoxby & Avery (2013) evaluate a nation-wide experiment that delivered customized information about admissions and financial aid to high-achieving, low-income students. The intervention positively affected applications, admission, and enrollment to selective colleges. These results catalyzed scholarship on information and advising interventions (Castleman & Goodman, 2018; Cunha, Miller, & Weisburst, 2018; e.g., Gurantz et al., 2021), but results have been mixed. Another set of studies evaluate interventions by flagship universities that combine outreach and financial aid (Andrews, Imberman, & Lovenheim, 2020; Dynarski, Libassi, Michelmore, & Owen, 2021).

A small number of studies from economics evaluate third-party products. Mulhern (2021) finds that customized information provided by Naviance college planning software causes students to apply to colleges where they have a high probability of admission and where their SAT scores are similar to previous admits, with affect sizes largest for Black, Hispanic, and low-income students. In a report by College Board, Howell et al. (2021) compared SAT test-takers who opted into the College Board Student Search Service – allowing accredited institutions to purchase their contact information – to those who opted out. After controlling for covariates (e.g., SAT score, parental education, high school), 41.1% of students who participated in Search attended a 4-year college compared to 32.8% of students who opted out, an 8.3 percentage point difference and a 25.3 (`(41.1-32.8)/32.8`) percent change in the relative probability. Participating in Search was associated with a larger change in the relative probability of attending a 4-year college for Black students (24.5%) and Hispanic student (34.4%) than White students (21.6%), and a larger change for students whose parents did not attend college (40.6%) than those whose parents had a BA (18.9%).[1] Leveraging a natural experiment in College Board student list purchases, Smith et al. (2022) find that the purchase of a prospect profile by a college increases the probability that the student will apply to and enroll at the college, with larger effects sizes for Black, Hispanic, and low-income students.

Scholarship from sociology tends to document recruiting behavior "in the wild," often as part of broader analyses of college access or enrollment management (Cottom, 2017; e.g., Posecznick, 2017). Holland (2019) probes the structural holes between high school counseling and college recruiting efforts from the perspective of high school students. Underrepresented minority students reported "feeling like their school counselors had low expectations for them and were too quick to suggest that they attend community college" (p. 97). In turn, these students were drawn to colleges that made them feel wanted, often attending institutions with lower graduation rates and requiring larger loans than other options.

Several studies analyze connections between colleges and high schools from an organizational perspective (Khan, 2011; Salazar, 2022; Salazar, Jaquette, & Han, 2021; Stevens, 2007). Off-campus recruiting visits have been conceptualized as an indicator of enrollment priorities (Salazar et al., 2021; Stevens, 2007) and/or a network tie indicating the existence of a substantive relationship (Author, XXXX). Stevens (2007) provides an ethnography of enrollment management at a selective liberal arts college. The college valued recruiting visits to high schools as a means of maintaining relationships with guidance counselors at feeder schools,

[1] After controlling for covariates, Howell et al. (2021) find that 20.6% of students who participated in Search obtained a BA in four years compared to 15.7% of students who opted out, representing a 31.2% increase in the relative probability of graduation and this increase was larger for Black (40.3%) and Hispanic (43.3%) students (48.3%) than it was for white students and larger for students whose parents did not attend college (50.0%) than it was for students whose parents had a BA (25.3%). The logical mechanism is that where students start college affects the probability of graduation (B. T. Long & Kurlaender, 2009; Melguizo, 2008).

and tended to visit the same set of – disproportionately affluent, private, and white – high schools year after year. Salazar et al. (2021) analyzed off-campus recruiting visits by 15 public research universities. Most universities made more out-of-state than in-state visits. These out-of-state visits focused on affluent, predominantly white public and private schools.

Cottom (2017) shows that for-profit colleges found a niche in Black and Hispanic communities precisely because traditional colleges ignored these communities (see also Dache-Gerbino, Kiyama, & Sapp, 2018). For-profits identified prospects by compiling and purchasing lists (Cottom, 2017). However, they did not rely on lists from College Board and ACT because their target audience of Black and Hispanic adult women were not recent test-takers. Ironically, Black and Hispanic adult women were vulnerable to marketing from for-profits because they were excluded from the College Board and ACT lists used by traditional colleges. The for-profit business model of encouraging students to take on federal and private loans exemplifies "predatory inclusion," the logic of "including marginalized consumer-citizens into ostensibly democratizing mobility schemes on extractive terms" (Cottom, 2020, p. 443). Another example of predatory inclusion is "payday loans," which target people with low credit scores based on data purchased from credit bureaus (Fourcade & Healy, 2013).

Reflecting on the recruiting literature, studies from both economics and sociology find that underrepresented student populations are particularly sensitive to recruiting. Economics often evaluates the effect of outreach designed to increase underrepresented student enrollment at selective colleges. By contrast, scholarship from sociology (Salazar et al., 2021; e.g., Stevens, 2007) and investigative reporting (MacMilan & Anderson, 2019; Tough, 2019) from the popular press consistently find that the recruiting efforts of selective colleges prioritize students from privileged schools and communities. While a few studies from economics analyze how students respond to interventions delivered by third-party products (Mulhern, 2021; e.g., Smith et al., 2022), scholarship from sociology assumes that recruiting is something done by individual colleges. However, no studies analyze third-party recruiting products as the fundamental object of analysis. We argue that third-party products and vendors structure college recruiting behavior and, in turn, college access. Prior research has not examined whether third-party recruiting products incorporate structural inequality in ways that systematically disadvantage underrepresented students. Prior research has not examined how colleges utilize these products. This study deconstructs the College Board Student Search Service product. We simulate the racial composition of purchases that utilize conceptually motivated search filters and we examine the usage of these filters in actual student lists purchased by public universities.

2.3 Background: Student List Products

List-based vs. behavioral-based leads. "Lead generation" is the process of connecting merchants who sell products to "leads" – consumers potentially interested in these products (Federal Trade Commission, 2016b). Student lists are an example of "list-based" lead generation. List-based lead generation is based on the direct mail business model (Singer, 1988) but has evolved into "database marketing," in which information about prospects is stored in a database and prospects are selected using search filters (e.g., Equifax, 2023). Behavioral-based targeting emerged from advances in digital technology and includes most advertising on websites and social media. Whereas list-based marketing proceeds in two steps – obtain customer contact information and then serve marketing material — behavioral-based targeting identifies targets based on their user profile and simultaneously serves advertisements to users while they are on the platform. An article on digital advertising by EAB (2018, p. 9) provides insight about usage of list-based and behavioral-based leads in higher education:

> For industries outside of higher education and for non-freshman recruitment, a primary aim of digital marketing is often that of identifying a pool of potentially interested customers ... [By contrast] Where the recruitment of college-bound high school students is concerned, digital channels are less important from a lead-generation perspective, because the vast majority of likely candidates are already readily identifiable via testing and survey services (ACT, College Board, etc.). Digital marketing is, instead, of greatest value in further stages of the recruitment funnel, including inquiry generation and application generation.

When recruiting college-going high school students, EAB (2018) suggests that behavioral-based leads are less effective than purchasing names from College Board/ACT and then targeting these prospects on digital platforms (e.g., Meta allows colleges to serve ads to purchased names on Facebook/Instagram). Behavioral-based targeting (e.g., Google Ads, Google Display Network, Twitter) is the primary sources of leads when high-quality databases of prospective customers are not available, such as programs targeting working adults (Carey, 2019; Ruffalo Noel-Levitz, 2022c).

Sources of student list data. Student list data are extracted from the user-data of students laboring on platforms (e.g., taking a test, searching for college). Historically, the student list business has been dominated by College Board and ACT, which derive student list data from their database of test-takers. In the 21st Century, advances in technology yielded new sources of student list data, particularly free online college search engines (e.g., Cappex) and college planning software sold to high schools used by high school students and guidance counselors (e.g., Naviance, Scoir) (Jaquette, Salazar, & Martin, 2022).

Who buys student lists. Extant knowledge about how colleges use student lists depends on market research by Ruffalo Noel Leviz, which publishes regular reports about recruiting practices based on survey responses from their clients (mostly public and private non-profit universities of mid-level size and mid-level selectivity). In an analysis of 120 4-year colleges, Ruffalo Noel-Levitz (2022b) reported that 87% of private and 86% of public institutions "purchase high school student names to generate inquiries and applicants" (p. 5). For public institutions, 20% purchased fewer than 50,000 names annually, 29% purchased 50-100K, 31% purchased 100-150K, and 20% purchased more than 150K names annually. Ruffalo Noel-Levitz (2022a) reports that purchasing names was the top ranked expenditure item in the undergraduate marketing and recruiting budget for both private and public institutions. In 2022, the average public institution allocated 15% of its budget to purchasing names (up from 12% in 2020), compared to 2% of its budget on behavioral-based leads.[2] Case studies and investigative reporting suggests that larger and more selective institutions purchase more names than smaller and less selective ones (Arcidiacono, Kinsler, & Ransom, 2022; Belkin, 2019; Jaquette et al., 2022). Even though selective/prestigious colleges receive many inquiries, they may buy names in order to increase applications (and lower acceptance rates) and/or to

[2]For private colleges, 16% purchased fewer than 50,000 names annually, 35% purchased 50-100K, 28% purchased 100-150K, and 21% purchased more than 150K names annually (Ruffalo Noel-Levitz, 2022b). In 2022 the average private institution allocated 16% of its budget to purchasing names (up from 14% in 2020), compared to 7% of its budget on behavioral-based leads (Ruffalo Noel-Levitz, 2022a).

increase enrollment of underrepresented populations.

Buying College Board and ACT student lists. Each student list purchase is a subset of prospects from a larger, underlying database. College Board, ACT, and other student list products (e.g., *Intersect*) incorporate search filters that allow customers to control which prospect profiles they select. Salazar, Jaquette, & Han (2022) categorizes search filters available in the College Board Student Search Service product into the four buckets of academic, geographic, demographic, and student preferences (e.g., desired campus size, intended major). Academic filters include high school graduating class, SAT score, PSAT score, AP score by subject, high school GPA, and high school class rank. Individual filters are specified as score ranges and can be combined with other filters as `AND` or `OR` conditions. Geographic search filters include state, CBSA, county, zip code, and "geomarket" and "geodemographic" filters (described below). Demographic filters include race, ethnicity, gender, and first-generation status. Student preference filters include intended major, college size, and college type. Analyzing data about 830 student lists purchased by 14 public universities, Salazar et al. (2022) found that the average list purchase specified 4.44 criteria and 98.8% of purchases specified at least one academic and one geographic filter.

A purchased list (College Board template, ACT template) is a spreadsheet with one row per prospect and columns for contact information and student characteristics from the pre-test questionnaire (e.g., graduation year, high school code, ethnicity, race, intended major). Information about academic achievement is very limited, but can be inferred from search filters.

How lists are used. Much like the role of voter files in political campaigns (Culliford, 2020), purchased lists are the basic building block for data-informed undergraduate "recruiting campaigns." Enrollment managers use predictive models to inform recruiting interventions (Ruffalo Noel Levitz, 2021; Salazar et al., 2022). However, both the algorithms and the interventions must be fed data about prospects (e.g., cannot send brochures and emails without addresses). Therefore, at the top of the enrollment funnel (Figure 1), colleges buy the contact information of prospects they want to recruit. Purchased lists are combined with student-as-first-contact inquiries and then layered with additional data sources, such as consumer data from credit bureaus, historical application/enrollment data about students who attended the same high school, etc. These layered data are the input to predictive models that inform decisions about recruiting interventions designed to push prospects to subsequent stages of the funnel (e.g., who gets a $0.50 postcard, a $7 brochure).

Ruffalo Noel-Levitz (2022b) reports that email, targeted digital advertising (e.g., Instagram), and direct mail are the top three methods for first contact with purchased high school names. Additionally, the average number of times purchased names are contacted before giving up is 8 and 11, respectively, for public and private institutions. With respect to efficacy, Ruffalo Noel Levitz (2018) asked clients to rate different "first contact" interventions (e.g., off-campus recruiting visit) as sources of inquiries and enrolled students. For the median public college, purchased lists accounted for 26% of inquiries, which ranked #1, and accounted for 14% of enrolled students, which ranked fourth after "application as first contact" (19%), campus visit (17%), and off-campus visit (16%).[3]

3 Conceptual Framework

ADD INTRO PARAGRAPH

3.1 Selection Devices

The sociology of race is concerned with processes that allocate individuals to categories based on some set of input factors. Examples include college admissions, hiring, applications for credit, and prison sentencing. Selection devices are procedures or routines for making selection decisions (Hirschman & Bosk, 2020). One dimension on which selection devices differ is individual discretion versus standardization. Discretionary selection processes rely on the judgment of individual evaluators. In professional domains (e.g., psychiatric treatment, holistic admissions), evaluators exercise judgment about cases based on professional norms about how to evaluate inputs. By contrast, "standardized selection devices" make decisions based on a mathematical function in which the value of input variables determines the value of the outcome (Duncan, Ohlin, Reiss, & Stanton, 1953), for example a public university that admits applicants based on a function of ACT score and GPA.

[3]For the median private college, student list purchases were the highest source of inquiries, accounting for 32% of inquiries and were tied with off-campus recruiting visits as the highest source of enrolled students, accounting for 18% of enrolled students (Ruffalo Noel Levitz, 2018).

Student list products are selection devices that enable university administrators to select prospective students from a larger pool based on a set of input factors. Student list products are discretionary rather than standardized selection devices. For each purchase, administrators choose which inputs to filter on and which thresholds to apply to each filter.

Scholarship examines whether discretionary and standardized selection devices produce/reduce racial inequality (Benjamin, 2019; e.g., Korver-Glenn, 2018; Norris, 2021). Burrell & Fourcade (2021, p. 22) observe that, following 1970s anti-discrimination legislation, many industries adopted standardized selection devices because "evidence had accumulated that both private and public decision-makers were routinely giving into vague intuitions, personal prejudices, and arbitrary opinions." Reviewing the literature, Hirschman & Bosk (2020) state that standardized selection devices can reduce racial inequality *if* the primary source of inequality is explicit or implicit racial bias from individual decision-makers.

Neither standardized nor discretionary selection devices eliminate racial inequality stemming from structural racism. Bonilla-Silva (1997) criticizes social science disciplines (e.g., psychology, economics) for defining racism as an ideology held by individuals. These definitions cast attention to the attitudes and behaviors of individuals, ignoring the possibility that broader institutions can be racist. Structural racism is "a form of systematic racial bias embedded in the 'normal' functions of laws and social relations" (Tiako et al., 2021, p. 1143), whereby processes viewed as neutral or common-sense systematically advantage dominant groups and disadvantage marginalized groups. Amidst the growth of "colorblind" selection devices that do not include race as an input, scholarship from sociology finds that selection devices may produce racial inequality by utilizing seemingly neutral or objective determinants that are systematically correlated with race (e.g., Benjamin, 2019; Norris, 2021).

Racialized inputs. Norris (2021) reconstructs Moody's city government credit rating algorithm, which assigns credits scores to cities based on determinants thought to predict loan default. Norris (2021, p. 5) defines racialized inputs "those that are theoretically and empirically correlated with historical racial disadvantage," subjugation, and exclusion. By contrast, non-racialized inputs are "theoretically and empirically orthogonal or distant from racial disadvantage." Median family income is conceptualized as a racialized input; because of historical wage discrimination, income is correlated with race and cities with a greater share of Black residents have lower median income. Once median income is included in Moody's model, percent Black is no longer a significant predictor of city credit rating. Through the inclusion of seemingly neutral racialized inputs, "prior disadvantage and racism against Black individuals becomes institutionalized" Norris (2021, p. 2) and selection devices yield racially disparate outcomes "in ways that escape legibility/cognition as racially unequal" Norris (2021, p. 5).

Geographic inputs. Geographic borders are the most commonly studied racialized inputs (Benjamin, 2019; Korver-Glenn, 2022; O'Neil, 2016). These studies build on the fact that American communities and schools are racially segregated as a consequence of historic and contemporary laws, policies, and practices promoting racial segregation (e.g., Harris, 1993; Korver-Glenn, 2018; Rothstein, 2017). Algorithmic selection devices that categorize people based on geographic location without considering structures that produce segregation are likely to reproduce historical race-based inequality in opportunity. For example, O'Neil (2016) analyzes an algorithm using zip code as an input to predict the probability of recidivism for previously incarcerated people. Because zip codes are correlated with race, using zip code to predict recidivism generates racial inequity in predicted risk.

Using geography as a predictive input was pioneered by geodemography, a branch of market research that estimates the behavior of consumers based on where they live (Burrows & Gane, 2006). Initial geodemographic systems scored individual localities based on consumer behavior. Subsequent systems (e.g., Mosaic by Experian) classify localities and individuals into like audience segments for marketers (Experian, 2023). Geodemography emerged in the 1980s alongside efforts to fuse marketing and credit scoring, at a time when businesses dependent on customer credit transitioned from approving/rejecting applicants to the more aggressive model of pre-approving desirable customers (Leyshon & Thrift, 1999). Richard Webber – director of Experian Marketing Services UK and creator of Acorn and Mosiac – has been called the "founder of geodemographics" (McElhatton, 2004). Webber (1988, p. 36) described the integration of credit scores and geographic information to recruit customers, which is similar to the process of integrating SAT scores and geographic filters in student list products:

> Geographical information can... be very useful at the recruitment stage. Addresses in postcodes with high levels of bad debt can be eliminated as can those where credit referencing activity is particularly low. Area classification systems, such as Mosaic and Acorn, yield further discriminators which can be used to reduce the recruitment of poor credit risks... The combination of all this information into a recruitment scorecard allows the credit operator to select the best possible addresses from rented lists, electoral rolls or the company's own customer file... and enables the recruitment of accounts to be redirected away from areas of high bad debt.

Predictive analytic inputs. Another class of racialized inputs come from predictive analytics, which have been a focus of scholarship on algorithmic bias (Burrell & Fourcade, 2021; e.g., Noble, 2018; Norris, 2021; O'Neil, 2016). Federal Trade Commission (2016a, p. 4) distinguishes selection devices that rely on "descriptive" analytics based on "features that exist in data sets" (e.g., high school GPA, gender), versus those that rely on predictive analytics, which "refers to the use of statistical models to generate new data" (e.g., predicted probability of recidivism). The creation of predictions proceeds in two steps: first, apply statistical models to previous cases to determine the predictors of an outcome; second, apply the results of these analyses to predict the outcome for future cases.

Predictive analytics are commonly utilized as the outcome variable in standardized selection devices. For example, algorithms assign credit scores to individuals (Poon, 2007) and to cities (Norris, 2021) based on analyses of predictors of default for past cases. Additionally, discretionary selection devices such as student list products utilize predictive analytics as another input to select on (Federal Trade Commission, 2014). For example, the ACT student list product offers the "Enrollment Predictor" search filter, which allows colleges to filter prospects based on their predicted probability of enrolling in your college (Schmidt, 2019). College Board uses predictive analytics to create new geographic filters (e.g., "Geomarket" filter, "Geodemographic Segment" filter), which essentially draw geographic borders for including/excluding future prospects based on analyses of the college-going behavior of past prospects (College Board, 2011). Whether predictive inputs are used as an outcome or an input, Burrell & Fourcade (2021, p. 224) state that "predicting the future on the basis of the past threatens to reify and reproduce existing inequalities of treatment by institutions." Harcourt (2007) refers to this phenomenon as the "ratchet effect," whereby disproportionately targeted/excluded populations are predicted to have higher risk of an outcome, which amplifies disproportionate targeting/exclusion.

3.2 Student List Products

Test-taking and test score filters. RQ1 examines the relationship between individual student list product attributes and racial inequality, independent of how colleges utilize student list products. We argue that the underlying architecture of student list products produce structural inequality in two broad ways.

The first source of structural inequality is which prospective students are included in the underlying database. Sample selection bias is a concern whenever individuals are excluded from a selection device or statistical model because of missing values for some or all variables. Jillson (2021, para 4) warns that missingness correlated with race results in systematic racial bias: "If a data set is missing information from particular populations, using that data to build a…model may yield results that are unfair or inequitable to legally protected groups."

Historically, College Board and ACT student list products exclude students who do not take at least one of their assessments (e.g,. SAT, AP, PSAT).[4] Prior research shows that rates of SAT, ACT, and AP test-taking differ by race (Blake & Langenkamp, 2022; e.g., Hyman, 2017; Kolluri, 2018). Additionally, Black students are more likely than white students to attend a high school with few AP course offerings (Rodriguez & McGuire, 2019). These findings motivate the following proposition:

P1: The condition of taking standardized assessments is associated with racial disparities in who is included versus excluded in student list products.

The second source of structural inequality in student list products is the use of racialized

[4] Recently, College Board and ACT, respectively, began allowing non test-takers to opt into student list products by participating in the College Board Big Future or the ACT Encourage college search engines, but it is unclear how many non test-takers opt in using these resources.

inputs as search filters, which builds on differences in who is in the underlying database and exacerbates differences in who is included in student list purchases. We argue that test score filters (e.g., SAT, PSAT, AP) meet the Norris (2021, p. 5) racialized input criteria of being "theoretically and empirically correlated with historical racial disadvantage." Race-based differences in standardized test scores are a function of historical and contemporary segregation of U.S. communities in schools (Reardon, Kalogrides, & Shores, 2019), which drive race-based differences in school funding (Green III, Baker, & Oluwole, 2021) and drive race-based differences in access to college preparatory curriculum, including SAT/ACT test preparation (Park & Becks, 2015) and access to AP courses (Kolluri, 2018; Rodriguez & Hernandez-Hamed, 2020). Therefore, filtering prospects based on test scores without simultaneously considering the historical and contemporary structural inequalities that drive race-based differences in test scores is likely to reproduce racial inequality in educational opportunity.[5]

P2: As test score threshold increases, the proportion of underrepresented minority students included in student lists declines relative to the proportion who are excluded.

Geographic filters. Geographic search filters enable colleges to target prospects based on where they live. College Board geographic search filters include state, CBSA, county, zip code, geomarket, and geodemographic filters. We conceptualize geographic search filters as racialized inputs because these filters are built on top of historic and contemporary policies and practices promoting racial segregation. Targeting prospective students based on geographic location without consideration to macro and local structures that produce racial segregation is likely to reinforce historical race-based inequality in educational opportunity.

Prior scholarship on recruiting (Author, XXXX; Salazar, 2022; Salazar et al., 2021; e.g., Stevens, 2007) and articles in the popular press (MacMilan & Anderson, 2019; Quirk, 2005; e.g., Tough, 2019) consistently find that selective private and public research universities disproportionately target affluent schools and communities. By contrast, for-profit colleges systematically target poor, communities of color (Cottom, 2017; Dache-Gerbino et al., 2018).

[5] By comparison, high school GPA is a strong predictor of postsecondary student success (Allensworth & Clark, 2020; Niu & Tienda, 2010) and is more theoretically and empirically distant from historical racial disadvantage (Alon & Tienda, 2007; Posselt et al., 2012).

Reporting by MacMilan & Anderson (2019) state that "consulting companies may estimate a student's financial position by checking their Zip codes against U.S. Census data for estimated household incomes in that area." Rivard (2013) reported that " 'Everybody wants to go to the magic island of full pay students, but it's rapidly shrinking real estate,' said Bill Berg, an enrollment management consultant at Scannell & Kurz" and that "College Board does sell zip codes, which are a very good proxy for income levels, meaning colleges and their consultants could use the data to sort out rich and low-income kids." Collectively, these studies and articles suggest that selective private colleges and public flagship universities may filter on affluent zip codes when purchasing student lists, while for-profits may filter on low-income, urban zip codes. We expect that filtering for affluent neighborhoods is positively associated with racial exclusion because structures of racial segregation often prohibit people of color from living in affluent neighborhoods.

P3. As purchases filter on higher levels of zip-code affluence, the proportion of underrepresented minority students included declines relative to the proportion excluded.

Many public universities filter on larger localities (e.g., county, state, CBSA) as means of targeting their local catchment area. We do not conduct analyses to this effect because this manuscript is primarily concerned with the potential for student list products to do harm. We would like to test propositions about the College Board Geomarket and Geodemographic Segment filters because scholarship raises concerns about filters that incorporate predictive analytics. We cannot recreate these filters using HSLS data because they rely on proprietary data, but we can examine actual student list purchases that utilized these filters.

3.3 Utilizing Student List Products

While the discussion so far has focused on individual filters, student list products are designed to filter on multiple search filters simultaneously and they grant administrators discretion over which filters to select and how many purchases to execute. Individual colleges may utilize student list products in ways that reduce or amplify racial inequality in college access. This section motivates analyses about how public universities utilize racialized search filters in concert with other search filters when purchasing student lists (RQ2) and about the racial composition of student list purchases that utilize multiple search filters (RQ3).

We highlight several findings from sociological scholarship on product utilization. First, on balance, scholarship tends to find that administrative discretion over selection devices causes structural inequality to increase (Castilla, 2008; Cotter, Medeiros, Pak, & Thorson, 2021; Norris, 2022). Discretionary selection devices are sensitive to racialized inputs and allow the explicit or implicit individual bias to affect selection decisions (Burrell & Fourcade, 2021; Korver-Glenn, 2018). For example, Korver-Glenn (2018) shows that Houston area homes in white neighborhoods received higher appraisal values than those in non-white neighborhoods because of appraiser discretion in selecting comparison homes, which is exacerbated by the racialized borders of housing market areas drawn by the real estate board. Second, discretionary selection criteria often reflect occupational or professional norms, which may conceive of racialized inputs as objective, colorblind measures of merit (Hirschman & Bosk, 2020; Krippner & Hirschman, 2022; Tiako et al., 2021). Third, empirical research shows that Americans dramatically underestimate the magnitude of racial income inequality (Kraus, Onyeador, Daumeyer, Rucker, & Richeson, 2019). Discretionary selection devices that incorporate racialized inputs may produce racial inequality because decision-makers may have incomplete knowledge about how these inputs interact with local patterns of racial inequality (Cotter et al., 2021; Korver-Glenn, 2018).

These findings motivate analyses about administrative discretion and racial inequality in student list purchases. First, colleges may select academic achievement filters based on admissions standards, which are a function of university stakeholders and the macro trends in the admissions profession (Clinedinst, 2019). Until quite recently, most admissions offices viewed test scores as objective measures of achievement or aptitude (Hoxby & Avery, 2013). Therefore, we expect that selective institutions are more likely to filter on standardized test scores compared to less selective institutions and are likely to filter on higher score thresholds.

However, the utilization literature suggests that admissions standards are not the sole driver of inequality in student list purchases. Prior scholarship finds that transparency – selection criteria are clear to all stakeholders – and accountability – utilizing biased selection criteria yields consequences are safeguards against unintentional and intentional racial inequality in discretionary selection devices (Castilla, 2008; Norris, 2022). The process of purchasing student lists is opaque to most internal and external stakeholders. There can be no accountability without transparency (Norris, 2022). Admissions readers are typically trained and normed before they evaluate applications (Bastedo, 2016). By contrast, any person affiliated with a Title IV institution can execute student list purchases. Furthermore, we could not find written professional norms about how to purchase lists. Without guardrails against discretion, the utilization of a powerful product is likely to yield unintended consequences, particularly when purchasers select on several complicated filters.

Filtering on multiple search filters facilitates micro-targeting of desired prospects, which has become a branding strategy for student list products. For example, College Board Student Search promises to "create a real pipeline of best-fit prospects" (College Board, n.d.) and consultancies encourage colleges to execute multiple student list purchases, each targeting different market segments (e.g., Waxman, 2019).[6] The flip-side of micro-targeting is exclusion (Cotter et al., 2021). Purchased lists do not show how the characteristics of targeted prospects compare to the demographics of their surrounding community. Thus, specifying multiple filters can yield unintended racial inequality because administrators have incomplete knowledge about how the intersections of these filters interact with local patterns of segregation. Considering a non-racialized filter (high school GPA), adding a racialized input filter (e.g., AP score) may increase racial inequality. Additionally, filtering on multiple structurally racist inputs (e.g., SAT score and zip-code) may have a compounding effect on racial inequality.

Third, College Board and ACT have added search filters based on predictive analytics (e.g., College Board "Geomarket", ACT "Enrollment Predictor"). The Geomarket filter sub-divides states/metropolitan areas into distinct markets based on historical data about college enrollment. Geodemographic Segment filters allocate individual census tracts and individual high schools into distinct clusters based on past college enrollment. Creating new geographic borders based on historical patterns amplifies the effect of historic race-based inequality (Burrell & Fourcade, 2021). Furthermore, administrators utilizing these filters have incomplete knowledge about how these borders interact with local patterns of segregation.

[6]In data collected by Salazar et al. (2022), colleges assigned names to individual searches, such as, "Women in STEM," "International 2022 PSAT 1200," "CA 2021 SAT URM to 1290," "Performing arts."

We expect that using Geomarket or Geodemographic filters, in concert with other search filters, is associated with racial inequality in targeted versus excluded prospects.

Colleges may utilize student list products to increase enrollment by underrepresented populations. College Board and ACT student list products are designed to facilitate this goal by incorporating filters for race, ethnicity, and first-generation status. For example, colleges may purchase separate lists for particular racial/ethnic groups, specifying different test score thresholds for different groups. Considering the complexity of student list products and incomplete knowledge about race-based income inequality (Kraus et al., 2019), student list purchases designed to overcome one inequality may unintentionally amplify other social inequalities. For example, purchases designed to target "women in STEM" may yield racial or socioeconomic inequality. Additionally, purchases that explicitly target underrepresented minority students with high test scores may systematically exclude students from predominantly non-white communities.

4 Methods

4.1 Data

Our analyses utilize two data sources. First, the primary data source is the High School Longitudinal Study of 2009 (HSLS09) conducted by the National Center for Education Statistics (NCES). HSLS09 is a nationally representative survey that follows a cohort of more than 23,000 students from 944 schools entering the ninth grade in Fall 2009. Follow-up surveys were administered to students in Spring 2012 (when most were in 11th grade), in 2013, in 2016, and NCES collected high school transcripts in 2013-14. HSLS provides the extensive student-level demographic, geographic, and academic variables needed to create academic and geographic filters used within student list purchases. We use HSLS09 to run analyses for RQ1 and RQ3.

Our HSLS09 analysis sample includes students who meet all of the following conditions: completed Spring 2012 first follow-up survey; completed 2013 update survey; and obtained high school transcript data. Of the 23,503 respondents included in HSLS09, our unweighted analysis sample consists of the 16,530 students who meet all conditions.[7] The survey weight variable W3W2STUTR is designed for respondents who meet these conditions. After weighting, these 16,530 students represent the population of approximately 4.187 million U.S. 9th graders in 2009.

Collected as part of a larger project (Salazar et al., 2022), the second data source consists of "order summaries" and their resulting "student lists" for College Board purchases by 14 universities. This link shows an example of a College Board summary for a student list purchase. These order summaries were converted into tabular data and used in analyses for RQ2. Order summaries were collected by issuing public records requests to all public universities in five states (CA, IL, TX, MN, and one anonymous state) about student lists purchased from 2016-2020. This public records request data collection included 830 College Board orders by 14 universities.

For RQ3 - analyzing the racial composition of lists that filter on multiple search filters - some analyses rely on HSLS09 data. For other analyses, we pull selectively from 414 orders - associated with 2,549,085 prospects- in our public records request data where we have both the order summary (i.e., which combinations of filters were used) and the prospect-level data (i.e., the resulting student list). This link shows some of the prospect-level data associated with ordered linked above. For more detailed information about data collect, see Salazar et al. (2022).

4.2 Variables

Dependent variable. Our primary dependent variable is prospects' race/ethnicity. For HSLS09, we use the student race/ethnicity composite variable X2RACE, which includes the following seven categories: American Indian/Alaska Native, non-Hispanic; Asian, non-Hispanic; Black/African-American, non-Hispanic; Hispanic; More than one race, non-Hispanic; Native Hawaiian/Pacific Islander, non-Hispanic; and White, non-Hispanic.[8] We select X2RACE based on recommendations by Viano & Baker (2020) to combine the measure of Hispanic ethnicity with the broader racial/ethnic variable to effectively measure and use

[7] All unweighted sample size numbers are rounded to nearest 10 to meet restricted data regulations by NCES

[8] We collapse "Hispanic, no race specified" and "Hispanic, race specified" into a single category.

race/ethnicity in analyses. For public records request data, College Board data have separate measures for race and ethnicity, which allow students to select more than one option as per changes to census reporting requirements. Similar to HSLS09, we aggregate this into a single race/ethnicity measure with the same seven categories listed above.

Independent variables. Independent variables are measures of student list filters. Choices about independent variables were based on our conceptual framework and the set of student list filters observed in our public records request data collection, shown in Figure 6. Our conceptual framework restricts analytic focus to academic filters and geographic filters.

Propositions **P1** and **P2** focus on academic filters. **P1** is concerned about which students take standardized assessments, which determines inclusion in the underlying College Board student list database. **P2** is concerned with test score thresholds utilized to filter prospects. For **P1**, we create dichotomous measures for each of the following assessments (input variables in parentheses) based on test score variables from the high school transcript file: PSAT/PreACT (X3TXPSATCOM); SAT/ACT (X3TXSATCOMP); any AP exam (variables with names that start with X3TXAP); and any STEM AP exam. For **P2**, we use these same input variables to create test score measures for PSAT/PreACT; SAT/ACT; highest AP exam score; and highest AP STEM exam score. We also create a measure of unweightehigh school GPA in academic courses (X3TGPAACAD), which is a question asked in the pre-test questionnaire of College Board assessments. [9] Consistent with how College Board filters work, **P2** variables are analyzed as categorical rather than continuous variables. To select thresholds for **P2** variables – for example, an SAT score thresholds of less than 1000, 1000+, 1200+, 1300+, etc. – we considered what the product allows, what we observed in orders collected via public records requests, and the goal of parsimony.

Proposition **P3** focuses on geographic filters. We create measures for student's school zip code by merging in data from the National Center for Education Statistics (NCES). Next, we

[9]Student's can self-report their high school GPA on College Board's SAT Questionnaire by selecting from a 12-point interval scale ranging from 0.00 (F) to 4.33 (A+) (Marini, Young, & Shaw, 2021). However, we are unsure whether the questionnaire asks students to specify the weighting-scale used. Because schools use various weight-scales for reporting GPA and students are likely to report according to their school-calculated GPA, we use unweighted HSLS09 GPA as a conservative approach to capturing included students via minimum filter thresholds.

attach income data to zip code by merging in data from the American Community Survey (ACS) 2012 5-year estimates.

4.3 Analyses

Analyses across all research questions utilize simple descriptive statistics. For RQ1, analyses compare the racial composition of included versus excluded HSLS09 prospects when an individual search filter is utilized in isolation. Given HSLS09 is nationally representative, we run appropriate statistical tests for comparing differences in included versus excluded students by race/ethnicity. Consider a hypothetical purchase of all prospects that took an AP STEM exam. We compare the racial composition of the included group to the racial composition of the excluded group. For example, Black students comprise 5% (`=90/1800`) of AP STEM test-takers and Black students comprise 11% (`=1560/14720`) of students who do not take an AP STEM exam. The test for difference in proportions compares whether the proportion of included prospects who identify as Black differs from the proportion of excluded prospects who identify as Black, and this test is run separately for each race/ethnicity group. Analyses for propositions P1 through P3, which answer RQ1, examine HSLS09 prospects included versus excluded based on individual filters in isolation.

RQ2 asks which search filters did public universities utilize. Analyses draw on order summaries for the 830 student list purchases across the 14 universities in our public records request data collection. We use counts and proportions of filters used across research (N=8) versus ma/doctoral (N=6) universities to describe broad patterns in how racialized input search filters are used in concert with other filters when purchasing student lists.

RQ3 examines the racial composition of student list purchases that utilize multiple search filters simultaneously. Choices about filters are informed by our theoretical framework. Analyses based on HSLS09 examine included versus excluded prospects by race/ethnicity when multiple filters are utilized.

We also analyze RQ3 using data from actual student lists purchased by public universities, selecting from purchases where we are able to obtain the order summary and the associated prospect-level data. In contrast to analyses based on HSLS09, analyses based on public records requests are unable to make inferences about the population of student list purchases.

We are also unable to make comparative inferences about excluded groups for analyses based on public records requests. We therefore leverage secondary data from NCES and ACS to show the characteristics of comparison or population groups (e.g., all high school graduates in the metropolitan area) relative to student lists collected that provide the characteristics of included prospects.

4.4 Limitations

This manuscript uses HSLS09 to recreate the College Board Student Search Service. One limitation is that HSLS variables for SAT test-taking and test scores also include ACT test-takers, with ACT scores converted to the SAT scale. The same is true for the PSAT and PreACT. The Student Search service includes students who take at least one College Board assessment, but we cannot differentiate between College Board and ACT test-takers, so our analyses incorrectly treat ACT test-takers as College Board test-takers. We considered restricting the analysis sample to states where the majority of students take the SAT rather than the ACT. We chose not to take this approach because the ACT "Educational Opportunity Service" student list product – now, named Encoura – includes academic and geographic filters that are nearly identical to the College Board filters that are the focus of this manuscript (Schmidt, 2022). Thus, analyses can be interpreted as who would be included/excluded by both College Board and ACT student list products via college entrance (i.e., SAT and ACT) and pre-college entrance (i.e., PSAT and preACT) exams.

Second, test-takers have the opportunity to opt-out of the College Board Student Search Service and the ACT Educational Opportunity Service but HSLS09 has no reasonable proxy for whether students opt-in or opt-out. Moore (2017) finds that 86% of ACT test-takers opt-in, but does not investigate the student characteristics associated with opting in. Third, the HSLS09 cohort pre-dates the increase in test-optional admissions policies and decline in test-takers which occurred since the onset of COVID19. This undermines the external validity of our findings with respect to current cohorts of high school students. That said, several for-profit vendors have developed student list products (e.g., Intersect by PowerSchool) poised to acquire market share ceded by College Board and ACT, and these products use filters that are similar to College Board and ACT products (Feathers, 2022). Fourth, we could not make measures for high school class rank, an academic filter, or for geomarket and geodemographic filters, which utilize proprietary College Board data.

5 Findings

5.1 Racial Composition of Individual Filters

We address RQ1 by first describing the racial characteristics of HSLS09 students who completed standardized assessments in comparison to those who did not, which would determine inclusion in the underlying College Board student list database. Figure 2 presents the racial/ethnic composition of prospects included (i.e., completed assessment) and excluded (i.e., did not complete assessment) across standardized tests. For example, the top left graph shows that more than 1.8 million prospects completed a college entrance exam and would have presumably been included in the College Board student list database. In comparison, more than 2.3 million prospects did not complete a college entrance exam and would be excluded from the database. White students make up 57% of included students who completed a college entrance exam and 47% of excluded students who did not. Online Appendix Table 3 reports statistical tests for proportions between included and excluded students by race/ethnicity. Differences in White student proportions across included and excluded prospects are statistically significant ($p<0.001$). While Asian and Multiracial students make up nearly equal proportions in both included and excluded prospects, Hispanic students make up only 17% of included prospects relative to 26% of excluded prospects ($p<0.001$). Black students similarly make up 12% of included prospects but 15% of excluded prospects ($p<0.001$).

Other standardized assessments resulted in similar included prospects that on average made up of larger proportions of White and Asian students and smaller proportions of Hispanic, Black, and American Indian/Alaska Native students than excluded groups, lending support for Proposition P1. For example, Figure 2 also shows the composition of included versus excluded prospects by AP exam completion in any subject on the top right panel. Similar to college entrance exams, White (54% versus 51%) and Asian students (8% versus 3%) make up statistically significant ($p<0.001$) larger proportions of included prospects. While an equal proportion of included and excluded students are Hispanic (22%), Black students make up a smaller share ($p<0.001$) of included prospects (8%) than excluded prospects (15%). When inclusion versus exclusion is determined by completing an AP exam in a STEM subject, total included students declines to nearly half (383,669) of those included via completing any AP exam. Moreover, Black (7% versus 14%), Hispanic (19% versus 22%), Multiracial (7% versus 14%), and American Indian/Alaska Native (0.2% versus 0.7%) students make up smaller statistically significant proportions of the included prospects relative to excluded prospects based on completion of an AP STEM exam.

Proposition P2 states that the proportion of underrepresented minority students included in student lists decline relative to the proportion who are excluded as assessment score thresholds increase. In order to test this proposition, we analyze the racial composition of included versus excluded HSLS09 students at minimum score thresholds commonly used across student list purchase orders for college entrance, pre-entrance, and AP exams. For example, Figure 3 presents these results for college entrance (top panel) and pre-entrance assessments (bottom panel). For the top left panel, each bar represents the racial composition of included prospects who completed an entrance exam and scored at the minimum threshold indicated. On the top right panel of Figure 3, each bar represents the racial composition of excluded prospects who did not complete an entrance exam in addition to students who did complete the exam but did not meet the minimum score threshold indicated. Statistical tests for differences in proportion for Figure 3 are reported in online appendices for space considerations.

As entrance exam score thresholds increase from less than 1000 to greater than 1400 in Figure 3, proportions of included White and Asian students increase while proportions of included Hispanic and Black students decrease. For example, White students make up a statistically significant ($p<0.001$) smaller share of included (47%) than excluded (53%) prospects scoring less than 1000 on an entrance exam, which results in an equal share of Hispanic students (22%) and a greater share of included Black students (19% versus 12%) relative to excluded prospects at this score threshold. However, Hispanic student proportions in included versus excluded prospects decrease to 12% versus 25% at scores greater than 1000, 9% versus 23% at scores greater than 1200, and down to 5% versus 22% at scores greater than 1400. Similarly, Black student proportions in included versus excluded prospects decrease to 6% versus 16% at scores greater than 1000, 4% versus 14% at scores greater than 1200, 2% versus 14% at scores greater than 1300, and down to making up 0% of included prospects at scores greater than 1400. These proportional differences across score thresholds are statistically significant ($p<0.05$) for both Hispanic and Black students (online appendix).

Pre-entrance exam results are also shown in Figure 3 for composite scores that range from 60 to 240 on a PSAT scale. [10] Similar to entrance exams, as pre-entrance exam composite score thresholds increase from less than 120 to greater than 220, proportions of included White and Asian students increase while proportions of included Hispanic and Black students decrease relative to excluded prospects. Figure 4 shows similar racial disparities in included versus excluded prospects across AP exam score thresholds, providing strong support for Proposition P2.

Proposition P3 states that as purchases filter on more affluent zip codes, the proportion of underrepresented minority students included in student lists will decline relative to the proportion who are excluded. To test this proposition, we analyze the racial composition of included versus excluded students when filtering by zip code median household income. In order to deal with median household incomes varying widely across the U.S., we categorized all zip codes into percentiles based on levels of median household income within their respective states. This approach also aligns with common ways in which student list orders purchase prospect's contact information by filtering on zip codes within specific states and metropolitan areas.

Figure 5 presents the racial composition of HSLS09 students included versus excluded in student list purchases when filtering based on their zip code percentile of affluence. The figure suggests that as zip code affluence increases, included prospects have larger proportions of White students and smaller proportions of Hispanic and Black students relative to excluded prospects. For example, Hispanic and Black students make up 31% and 27% of included

[10] PSAT exams taken 2014 or before receive composite scores that range from from 60 to 240. PSAT exams taken 2015 or later are scored via a range from 320 to 1520. Our lower bound PSAT composite score thresholds of 120, 170, 200, and 220 for HSLS students who completed the exam prior to 2014 equate to minimum score thresholds of 890, 1220, 1410, and 1510 on the 2015 or later PSAT scale, respectively. For details, see College Board (2015).

prospects and 20% and 11% of excluded prospects at zip codes below the 20th percentile of affluence, respectively. The proportions of Hispanic and Black students within included prospects decline as zip code affluence increases up though the 89th percentile. For zip codes in 90th percentile or higher, the proportions of Hispanic students decline to 13% ($p<0.001$). Similarly, Black students make up 8% of included prospects relative to making up 15% of excluded prospects ($p<0.001$) within the most affluent zip codes. [11] These findings suggest that purchases filtering on higher levels of zip-code affluence lead to smaller proportions of underrepresented minority students included in student lists relative to the proportion who are excluded, providing support for Proposition P3.

5.2 Utilizing Student List Products

To answer RQ2, in what ways do public universities use racialized input search filters, we analyze how often filters were used for College Board students list purchases by the 14 universities in our public records request data collection.

Figure 6 illustrates the prevalence of each individual filter by institution type. We categorize filters within academic, geographic, demographic, and student preference groups. Both research and ma/doctoral universities commonly used academic filters like GPA, SAT, and PSAT. However, compared to ma/doctoral universities, research universities were less likely to filter on GPA or PSAT score and more likely to filter on SAT score. Additionally, AP filters were only used by research universities. Geographic filters used to purchase student lists also differed across institution type. Orders by research universities were more likely to use a state filter whereas ma/doctoral universities were more likely to use a zip code filter. Research universities also used filters utilizing predictive analytics to make inferences about the college going behavior of prospective students living in specific geographic areas (e.g., geomarket, segment). Research universities also used demographic and student preference filters. Filters for race, low socioeconomic status, and gender were the most commonly used demographic filters, whereas college size, major, college type, and location were the most commonly used student preferences.

[11] Online appendices report statistical tests for proportions between included and excluded students by race/ethnicity for zip code affluence.

Given the prevalence of academic filters across universities, Figure 7 and Figure 8 show minimum and maximum thresholds used in SAT and PSAT score filters by institution type, respectively. These figures show that research universities tended to specify higher minimum score thresholds and higher maximum score thresholds across both SAT and PSAT compared to ma/doctoral universities.

Student list purchases typically filter on multiple criteria. Table 1 shows the top ten filter combinations used for student list purchases across institution type for the 14 universities in our public records request data collection. [12] For ma/doctoral universities, the top 10 filter combinations account for 96% of all orders. This is a function of nearly half of all orders using a combination of high school graduation class, GPA, PSAT scores, and zip code as filters and another 33% of orders using the same filters with SAT scores instead of PSAT. For research universities, the top ten filter combinations account for 60% of all orders. The most common filter combination, making up 19% of all orders, included high school graduation class, GPA, SAT, and zip code. The second most common combination the same filters along with PSAT, high school rank, state, and race. The remaining top orders also used these filter combinations in addition to filters like low-socioeconomic status, AP scores, Geomarket, Segment, and gender.

5.3 Racial Composition of Multiple Filters

Analyses Based on HSLS09. Our last research question focuses on assessing the racial composition of student list purchases that utilize racialized input search filters in concert with other search filters. We begin by analyzing the racial composition of included versus excluded groups when filtering the HSLS09 sample based on common combinations of filters used by public and ma/doctoral universities in Table 1. For example, the top panel of Figure 9 shows included versus excluded prospects resulting from combining the two most common academic filters: GPA and college entrance and pre-entrance exams. Drawing on our conceptual framework, high school GPA is a strong predictor of postsecondary student success (Allensworth & Clark, 2020) and is less likely to be theoretically and empirically

[12] While the majority of orders specified multiple filters as "AND" conditions, some orders specified particular filters as "OR" conditions (e.g., SAT score in some range or PSAT score in some range). Additionally, filter combinations are skewed by universities that made large numbers of orders relative to other universities

correlated to racial disadvantage than standardized test scores (Alon & Tienda, 2007; Posselt et al., 2012). On the other hand, universities may filter on test score thresholds that are consistent with their admissions standards (e.g., more prestigious universities recruit and enroll students with higher test scores) (Clinedinst, 2019) but hold race-based differences driven by structural inequality. We therefore explore the racial composition of prospects included in student lists when filtering on GPA greater than or equal to 3.0 while simulating increases to minimum thresholds for standardized tests.

The left panel of Figure 9 presents the racial composition of prospects included when filtering on GPA greater than or equal to 3.0 across college entrance exam thresholds at increments of 50 beginning at scores just above the HSLS09 sample median of 1010. For space considerations, we do not present the plot for excluded prospect groups across all thresholds but include a column showing the racial composition of the HSLS09 sample. The figure suggests that even at the lowest college entrance exam score threshold, White students make up much larger proportions of included prospects while Black and Hispanic students make up significantly smaller proportions when filtering for both GPA and entrance exam scores. For example, White students make up 72% of included prospects when filtering for GPAs greater than or equal to 3.0 in combination with entrance exam scores greater than 1050, whereas Hispanic and Black students make up 10% and 3%, respectively. Racial disparities only grow as score thresholds increase. Moreover, these racial disparities are greater than when filtering at similar thresholds for entrance exam score (Figure 3) alone. The right panel of Figure 9 suggest Hispanic and Black students make up decreasing proportions of included students when combining a GPA filter greater than or equal to 3.0 and a pre-college entrance exam filter, whereas the proportions of White and Asian students increase. Although, we do not see the same disparities. Online appendices also show similar racial disparities are evident when filtering on both GPA and AP scores (Figure 14).

In order to assess the effects of combining academic and geographic racialized inputs together, Figure 10 adds a zip code affluence filter to the GPA and college entrance/pre-entrance exam order simulations presented above from HSLS09. We again deal with median household incomes varying widely across the U.S. by categorizing all zip codes into percentiles based on levels of median household income within state. The left panel of Figure 10 presents the racial composition of included students when filtering for GPAs greater than or equal to 3.0, college entrance exam scores greater than or equal to 1050, and zip codes at various levels of affluence. In comparison to racial disparities in included versus excluded prospects driven by just zip code affluence in Figure 5, the combination of zip code affluence with GPA and pre-entrance exam filters leads to greater disparities even at lower levels of affluence. For example, Figure 10 shows White students make up 72% of included prospects when filtering for GPAs greater than or equal to 3.0 in combination with entrance exam scores greater than 1050 within the lowest income zip codes (<20th percentile), whereas Hispanic and Black students make up 9% and 7%, respectively. The proportions of Hispanic and Black included prospects resulting from the combination of filters are considerably lower than the 31% of Hispanic and 27% of Black included prospects resulting from only filtering by zip code affluence (Figure 5). Greater racial disparities result from the the combination of filters across all levels of zip code affluence in comparison to only filtering by zip code affluence. Similar patterns are evident when combining similar zip code affluence and GPA filters with a pre-entrance exam filter for composite scores greater than or equal to 150.

Analyses Based on Collected Student List Purchases. By drawing on student lists purchases from our public records request data collection, we can explore the effects of utilizing filters beyond admissions standards. For example, while this study is unable to use HSLS09 to recreate predictive analytics filters that subdivide geographic areas into distinct markets based on past college enrollments to microtarget prospective students, we can analyze the racial composition of student lists using filters like College Board's Segment services via our project sample. College Board's segment filter merges demographic, academic, and historical college-going data from geographical areas to create predictive profiles for current college bound students (College Board, 2011b), which then categorizes every U.S. Census tract into one of 33 "neighborhood clusters" and every high school into one of 29 "high school clusters" based on these predictive profiles. Online appendix Table 9 and Table 10, recreated from College Board (2011b), show the characteristics of Segment neighborhood clusters and school clusters used as filters by one university in our project sample. Drawing on our conceptual framework, Table 9 and Table 10 suggest that predictive analytics used to create clusters are likely drawing on historical and geographical correlations between racial and income demographics. For example, neighborhood cluster EN78 is 26% nonwhite and has median income of $134,400 while neighborhood cluster EN:71 is 97% nonwhite and has median income of $42,661.

We therefore analyze the racial composition of student lists from eight orders by a public research university that utilized Segment filters and in concert with academic filters. These eight orders targeted 2019-2023 high school graduating classes, and resulted in 131,562 prospects whose profiles were purchased. All eight Segment orders filtered on GPAs ranging from a low of B- to a high of A+. The orders specified minimum SAT and PSAT scores that ranged from 1220-1240 on an SAT scale, whereas maximum PSAT and SAT scores were filtered at 1450. These student list purchases were also geographically filtered by state, CBSAs, and Segment. All eight orders filtered on the same Segment high school and neighborhood clusters, which are highlighted in online appendices Table 9 and Table 10. [13]

Figure 11 compares racial (and income) characteristics of prospects whose profiles were purchased via Segment to the characteristics of all public high school students in the top four metropolitan areas where the most prospect profiles were purchased from: New York (27,932 prospects, rank #1), Los Angeles (12,307 prospects, rank #2), Philadelphia (9,126 prospects, rank #3), Washington, DC (5,728 prospects, rank #4). For each metropolitan area, we show two figures: on the right column, we show the racial composition of prospects from the metropolitan area whose profiles were purchased compared to the racial composition of all public high school students in the metropolitan area; on the left column, we show the income of prospects whose profiles were purchased – defined as the average median household income of prospects' home zip codes– compared to the overall median income of the metropolitan area.

[13] All orders filtered for the following school and neighborhood clusters combinations: 1) Neighborhood cluster 51, with any high school cluster; 2) Neighborhood cluster 53, with high school cluster 70; 3) Neighborhood cluster 58, with any high school cluster; 3) Neighborhood cluster 60, with high school clusters 65, 70, or 79; 4) Neighborhood cluster 61, with high school cluster 65; 5) Neighborhood cluster 63, with high school clusters 68 or 70; 6) Neighborhood cluster 69, with high school clusters 65 or 79; 7) Neighborhood cluster 70, with high school clusters 65, 68, 70, or 75; 8) Neighborhood cluster 73, with any high school cluster; 9) Neighborhood cluster 78, with high school cluster 66; 10) High school cluster 79, with any neighborhood cluster.

For New York, Figure 11 shows White and Asian students comprised 58% and 27% of prospects whose profiles were purchased via Segment, respectively, compared to making up 30% and 9% of students in public high schools in the metropolitan area. By contrast, Black and Hispanic students comprised just 1% and 8% of prospects, respectively, compared to 26% and 34% of students in public high schools. Furthermore, prospects whose profiles were purchased lived in zip codes that were much more affluent – an average of $153,000 – than the overall New York metropolitan area median income of $91,000. Figure 11 shows similar racial and income patterns in the other three metropolitan areas.

Figure 12 takes a spatial look at the high schools presented in Figure 11 across the four metropolitan areas. The map shows public high schools, with blue markers indicating the location of a school where at least one prospect's profile was purchased and the size of blue markers indicating the number of prospects whose profiles were purchased. Red markers indicate the location of schools where no prospect profiles were purchased. Figure 12 corroborates findings presented for HSLS09 above. Prospects whose profiles were purchased attend high schools that are largely concentrated in affluent and predominantly White zip codes bordering the central cores of each metropolitan area, whereas schools where zero prospect profiles were purchased are concentrated in the lowest income communities with larger proportions of People of Color located in the center metropolitan areas. Similar patterns are evident across maps for all four metropolitan areas. Interactive versions of metropolitan maps for segment analyses can be accessed here.

We also draw on our public records request data collection to explore how universities may utilize student list products to increase enrollment by underrepresented populations. For instance, some universities in the study made orders targeting prospective students who are women interested in science, technology, engineering, and math (STEM) via two different filter combinations. The first combination used SAT scores, GPA (ranging from a low of B and high of A+), a state filter (in-state versus out-of-state), and prospects' self-reported intended major. SAT score filters for these orders ranged from 1200 to 1600 for in-state prospects and 1300 to 1600 for out-of-state prospects. The second pattern also used the same GPA and state filters, but STEM interest was proxied via AP test scores. Orders for in-state prospects filtered for scores ranging from 3 to 5 on AP STEM tests whereas orders for out-of-state prospects filtered for scores ranging from 4 to 5 on AP STEM tests.

We analyze the resulting student lists from these "Women in STEM" orders – focusing on prospects from four metropolitan areas – from one public research university in order to analyze in-depth patterns in the racial and economic characteristics of prospects that result from the combination of achievement, geographic, and gender filters used to target women interested in STEM. Because nearly 85% of prospects from Women in STEM orders were out-of-state prospective students (N=10,668), we select four out-of-state metropolitan areas and compare prospective students to the characteristics of public high school women students in those metropolitan areas. [14]

Figure 13 compares racial and income characteristics of prospective students whose profiles were purchased to the characteristics of all women public high school students in each metropolitan area. For each metropolitan area, we show two figures. The figure on the left column provides the average median household income for the overall metropolitan area, for prospects whose profiles were purchased using AP scores, and prospects whose profiles were purchased using SAT scores. The figure on the right column provides the racial/ethnic composition of all public high school women 12th grade students in the metropolitan area, of prospects whose profiles were purchased using AP scores, and of prospects whose profiles were purchased using SAT scores.

For New York, Figure 13 shows women attending public high schools in metropolitan area are 29% White, 9% Asian, 26% Black, and 34% Hispanic. However, women in STEM prospects from New York that scored a 4 or 5 on an AP STEM exam whose profiles were purchased by the university are 38% White, 44% Asian, 3% Black, 11% Hispanic, 5% multiracial. Only 2 women in STEM prospects in the New York metropolitan area whose profiles were purchased via AP scores identified as Native American. These racial disparities are most pronounced in orders using SAT scores. Of the 821 prospects from New York that scored a 1200 to 1600 on the SAT and indicated an interest in STEM majors, 54% were White, 43% were Asian,

[14] The four out-of-state metropolitan areas were selected based on where the greatest number of prospects whose profiles were purchased and based on regional variation: New York (1,663 prospects, rank #1), Atlanta (548 prospects, rank #2), Chicago (485 prospects,rank #3), and Seattle (279 prospects, rank #11).

and 3% were multiracial. Only one of the 821 prospects identified as Hispanic and zero prospects identified as Black or Native American. Similar patterns in the racial composition of Women in STEM prospects are evident across Atlanta, Chicago, and Seattle metropolitan areas. Figure 13 also shows Women in STEM prospects are also on average substantially more affluent than the rest of the metropolitan areas where they live.

6 Discussion

6.1 Summary

Racial inequality in college access remains an enduring challenge for policymakers concerned about equality of opportunity. The market for college access depends on students knowing where they want to enroll and colleges knowing who they want to enroll. Student lists are a match-making intermediary connecting colleges to prospective students. Recent research suggests that participating in student list products positively affect college access, with stronger effects for underrepresented students (Howell et al., 2021; Moore, 2017; Smith et al., 2022). However, the underlying architecture of student list products may incorporate structural inequality in ways that systematically disadvantage underrepresented students.

This manuscript investigates College Board student list search filters, how those filters are utilized, and the racial composition of students who are included versus excluded in student list purchases. We develop a conceptual framework by drawing from the sociology of race. We argue that several academic and geographic search filters are "racialized inputs" (Norris, 2021), which are correlated with race because of historical, race-based exclusion from the input. We recreate selected College Board search filters using a nationally representative sample of 9th graders from 2009. Results for proposition P1 show that conditioning on college entrance exam test-taking (SAT/ACT, PSAT/PreACT, and/or AP), results in racial disparities in students included in the underlying student list database. Filtering on higher test-score thresholds (P2) is associated with larger proportions of white and Asian students and smaller proportions of Black and Hispanic students being included in student list purchases. Additionally. filtering on higher levels of zip code affluence (P3) is associated with higher proportions of white students and lower proportions of Black and Hispanic students included.

Actual student list purchases select multiple search filters simultaneously. Analyses based on HSLS09 suggest filtering on multiple criteria across score thresholds (GPA and SAT/PSAT, GPA and AP) can have a compounding effect on racial disparities between included versus excluded prospects, which could be construed as a function of admissions standards. However, student list products are discretionary rather than standardized selection devices. Analyses based on student list purchases from our public records request data collection provide additional support for product utilization literature that suggests administrator discretion likely increases racial inequality. Relative to the population of public high school students across metropolitan areas, combinations of academic and geographic predictive analytic filters (Segment orders, Women in Stem orders) resulted in dramatic disparities in the number of Black and Hispanic prospects included in student list purchases.

In short, filters are powerful, complicated products that incorporate structurally racist inputs, and any person affiliated with a Title IV institution can execute student list purchases. However, specifying multiple filters can easily yield unintended racial inequality because administrators may have incomplete knowledge about how these filters intersect with local patterns of segregation.

6.2 Policy Implications

Federal policy. We observe striking parallels between the functions of consumer credit reports and student list products. Credit scores are designed to predict the probability of repayment, thereby overcoming "the chronic problems of information asymmetries" (Leyshon & Thrift, 1999, p. 434) by enabling firms dependent on customer credit "to distinguish 'good' from 'bad' customers 'at-a-distance' " (Leyshon & Thrift, 1999, p. 434). Similarly, in the market for college access, SAT/ACT scores were viewed as a measure of achievement or aptitude that helped create a national higher education market by enabling colleges to make apples-to-apples comparisons between applicants from different places (Hoxby, 1997, 2009). Consumer reporting companies like Equifax (2023) wrap credit scores, geographic information, and other consumer information into products that filter prospective customers, enabling firms to transition from approving/rejecting applicants to the more aggressive model of pre-approving desirable customers (Leyshon & Thrift, 1999). Similarly, student list products filter prospects by academic achievement, geographic location, and other characteristics.

Consumer credit report products are regulated under the Fair Credit Reporting Act (enforced by the FTC) and the Consumer Finance Protection Act (enforced by the Consumer Finance Protection Bureau) because these products lead to the extension of credit. We argue that student list products systematically lead to the extension of credit. At the top of the enrollment funnel (Figure 1), colleges obtain the contact information of prospective students by purchasing student lists. These purchased leads are systematically targeted with recruiting interventions designed to maximize the probability of conversion in subsequent stages of the enrollment funnel. At the end of the funnel, admits are offered financial aid packages – including loan aid – designed to increase the probability of enrollment. Student loans are the second highest source of debt in the U.S (Lee, 2013). Clearly, there is a systematic link between student list products and student debt and, therefore, a compelling rationale for federal regulation of student list products and student list vendors.

Historically, the U.S. Department of Education has focused on regulating Title IV institutions (direct providers) and "third-party servicers" that administer federal financial aid. The US Department of Education (2023a) "Dear Colleague" letter broadened the definition of third-party servicers to include entities that "interact with prospective students for the purposes of recruiting or securing enrollment." Although the regulations clearly target the activities of online program managers (OPMs), it remains unclear whether they cover student list vendors and products. Given that these regulations seek "to identify and remedy the root causes of unaffordable debts" (US Department of Education, 2023b), we recommend that the definition of third-party servicers be revised to include student list vendors, which are the root intermediaries linking students to Title IV institutions.

State policy. State policymakers are positioned to develop "public option" alternatives to private, third-party student lists products. This idea is inspired by national voter databases used in political campaigns, which are based on voter files collected by local and state governments (Culliford, 2020). Similarly, we argue that states can create student lists from statewide longitudinal student data systems, which contain information about academic achievement and contact information. Students and their parents would have the opportunity to opt in or opt out. Importantly, colleges would receive the contact information and academic achievement of students who opt in for free. Therefore, the public option would have no need for search filters that help colleges micro-target the "right" students. After obtaining the lists, the college could decide which prospects receive which recruiting interventions. Jaquette & Salazar (2022) provide more detail about essential product features and challenges to overcome.

Our proposed public option complements the adoption of direct admissions policies by state policymakers. Similar to the model of pre-approving customers in consumer markets, direct admissions policies make proactive admissions offers to high school students that meet admissions criteria. Odle & Delaney (2022) report that five states have adopted direct admissions or are considering adoption. Analyses by Odle & Delaney (2022) found that adoption by Idaho increased first-time undergraduate enrollment at the campus-level and the state-level. Brown & Burns (2023) state that identifying eligible students and their contact information is a significant barrier to equality of opportunity in direct admissions. To date, privately-led and state-led direct admissions policies rely on student lists purchased from third-party vendors. To make sure all eligible students in the state are included, Brown & Burns (2023) recommend that states adopting direct admissions should develop student lists based on state longitudinal data systems. At present, one state higher education system informed us that they are creating a student list product based on Jaquette & Salazar (2022) as part of their broader effort to implement a direct admissions system.

6.3 Implications for Scholarship

Scholarship on recruiting largely assumes that recruiting is done by individual colleges. Although Smith et al. (2022) analyze the effect of a college purchasing a prospect profile on the prospect's college choice, prior research has not investigated how the underlying architecture of student list products makes prospects more or likely to be targeted. As the first manuscript to focus on student list product architecture and utilization, we developed a broad conceptual framework to create scaffolding for more targeted research.

Future research should examine filters based on predictive analytics, which model past cases to make predictions about future cases. The analysis of Moody's city government credit rating algorithm by Norris (2021) suggests that these filters can be recreated – or closely approximated – using publicly available data sources. Manuscripts that analyze a single filter can yield broader insights about the implications of predictive analytics. One example is ACT's "Enrollment Predictor" filter, in which "every student in the Encoura®Data Cloud is scored on their likelihood to enroll at your institution" (Schmidt, 2022). College Board developed several geographic filters that create geographic borders based on historic, proprietary data on college enrollment. The "geomarket" filter carves metropolitan areas into distinct markets. Geodemographic segment filters utilize cluster analysis to allocate individual high schools and individual census tracts into distinct clusters based on historic college-going behavior. In 2021, College Board (2021) released three new "Environmental Attributes" geodemographic search filters that allocate individual high schools to categories: (1) Travel Rates (out of state); (2) Travel Rates (distance from home); and (3) AP engagement rates.

Another topic for future research is demographic search filters, which allow colleges to target prospects by race, ethnicity, sex, and first-generation status. The equity rationale is that these filters facilitate access for underrepresented populations, particularly in a post affirmative action landscape. However, purchases that target one inequity may reproduce others. For example, depending on the set of filters selected, purchases that filter for underrepresented racial/ethnic groups may disproportionately target students from affluent, predominantly white schools and communities. Demographic search filters may be the subject of future legal debate. The role of scholarship is to analyze demographic filters systematically so that legal and policy debates are based on empirical evidence. Following Arcidiacono et al. (2022), future research should compare the student list purchases of an institution to their admissions standards. Arcidiacono et al. (2022) found that Harvard purchased names of African American prospects who were unlikely to be admitted. How widespread is "recruit to reject" and for which prospects? Another issue, do colleges filter on academic criteria (e.g., SAT/ACT scores) that are no longer admissions criteria?

Future research should examine recent dynamics in the market for student list data. While a growing number of states require high school students to take the SAT or ACT (Gewertz, 2019), the diffusion of test-optional admissions policies may reduce the number of test-takers from other states who are included in College Board/ACT student list products. New sources of student list data – particularly online college search engines and college planning software purchased by high schools – and new student list vendors (e.g., PowerSchool) have entered the market. Second, The distinction between student list vendor and consultant is disappearing. Both College Board and ACT offer enrollment management consulting services. At the same time, large enrollment management consulting firms (e.g., EAB, Ruffalo Noel Levitz) have become student list vendors. Third, rather than selling names at a price per-prospect, the emerging trend is to wrap a proprietary database of prospects within a software-as-service recruiting products (e.g., EAB's Enroll360) that colleges must purchase in order to obtain access to these prospects. Jaquette et al. (2022) describe these dynamics in greater detail.

Finally, we hope that this manuscript motivates critical education policy research that focuses on third-party products and vendors more broadly. Schools and colleges have become increasingly reliant on third-party digital platforms that "enable multiple interactions between data, software code and a range of heterogeneous actors" (Perrotta, 2021, p. 54). The nascent platform studies in education literature draws from multiple disciplines to "explore the consequences of these innovations," urging scholars to "go beyond pedagogical and technical questions toward social, political, and economic critiques" (Napier & Orrick, 2022, p. 207). However, this literature has not yet investigated how third-party products and vendors structure educational opportunity along racial, class, and geographic dimensions.

For example, future research should examine how college access is structured by enrollment management consulting firms. Anecdotally, in our public records data collection, roughly half the public universities outsourced student list buys to consulting firms (Salazar et al., 2022). Several enrollment management consultancies sell algorithmic products designed to make recommendations about list buys (Fire Engine RED, 2022; Ruffalo Noel Levitz, 2021). For example, one product from Ruffalo Noel Levitz recommends how many names a college should buy from each zip code (James Madison University, 2017). These firms also serve recruiting interventions to purchased names (Jaquette et al., 2022). Beyond recruiting, consultancies advise on tuition pricing, and financial aid. However, extant scholarship on college access assumes that colleges perform these functions in-house. To the extent that colleges outsource enrollment management to consultancies, these consultancies substantially structure which students are funneled to which institution, and the financial aid offers they receive. Scholarship can inform how enrollment management consulting firms are incorporated into The US Department of Education (2023b) third-party service regulations.

7 References

Ahn, T., & Dominguez-Villegas, R. (2022). A change of plans: How the pandemic affected students of color and their plans for higher education. *University of California Los Angeles Latino Policy and Politics Institute*, 284–284. Retrieved from https://latino.ucla.edu/research/fact-sheet-education-covid/

Allensworth, E. M., & Clark, K. (2020). High school GPAs and ACT scores as predictors of college completion: Examining assumptions about consistency across high schools. *Educational Researcher*, *49*(3), 198–211. https://doi.org/10.3102/0013189X20902110

Alon, S., & Tienda, M. (2007). Diversity, opportunity, and the shifting meritocracy in higher education. *American Sociological Review*, *72*(4), 487–511. Journal Article. Retrieved from <Go to ISI>://000248696500001

American Association of Collegiate Registrars and Admissions Officers. (2018). Overlooked inefficiencies in admissions that can impact yield. Retrieved from https://www.aacrao.org/research-publications/research/eye-on-research-blog/article/aacrao-consulting/2018/05/03/overlooked-inefficiencies-in-admissions-that-can-impact-yield

Andrews, R. J., Imberman, S. A., & Lovenheim, M. F. (2020). Recruiting and supporting low-income, high-achieving students at flagship universities. *Economics of Education Review*, *74*, 101923. https://doi.org/https://doi.org/10.1016/j.econedurev.2019.101923

Arcidiacono, P., Kinsler, J., & Ransom, T. (2022). Recruit to reject? Harvard and african american applicants. *Economics of Education Review*, *88*. https://doi.org/10.1016/j.econedurev.2022.102255

Author. (XXXX).

Baker, R., Klasik, D., & Reardon, S. F. (2018). Race and stratification in college enrollment over time. *AERA Open*, *4*(1), 2332–8584. https://doi.org/10.1177/2332858417751896

Bastedo, M. N. (2016). Cognitive repairs in the admissions office.

Bastedo, M. N., Howard, J. E., & Flaster, A. (2016). Holistic admissions after affirmative action: Does "maximizing" the high school curriculum matter? *Educational Evaluation and Policy Analysis*. Journal Article. https://doi.org/10.3102/0162373716642407

Belkin, D. (2019). For sale: SAT-Takers' names. Colleges buy student data and boost exclusivity. *The Wall Street Journal*. Retrieved from https://www.wsj.com/articles/for-sale-sat-takers-names-colleges-buy-student-data-and-boost-exclusivity-11572976621

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new jim code*. Medford, MA: Polity.

Blake, M. K., & Langenkamp, A. G. (2022). Differences between latinx and white students in college-going behaviors. *Research in Higher Education*, *63*(2), 248–270. https://doi.org/10.1007/s11162-021-09648-6

Bonilla-Silva, E. (1997). Rethinking racism: Toward a structural interpretation. *American Sociological Review*, *62*(3), 465–480. https://doi.org/10.2307/2657316

Brown, L., & Burns, R. (2023). *The link between student lists and direct admissions: Pros, cons, and policy implications*. State Higher Education Executive Officers.

Burrell, J., & Fourcade, M. (2021). The society of algorithms. *Annual Review of Sociology*, *47*, 213–237. Journal Article. https://doi.org/10.1146/annurev-soc-090820-020800

Burrows, R., & Gane, N. (2006). Geodemographics, software and class. *Sociology-the*

Journal of the British Sociological Association, *40*(5), 793–812. Journal Article. https://doi.org/10.1177/0038038506067507

Campbell, A. (2017). *Higher education marketing: How to master your admissions funnel*. Hop Online. Retrieved from https://hop-online.com/blog/higher-education-marketing-admissions-process/

Carey, K. (2019). The creeping capitalist takeover of higher education. *HuffPost*. Retrieved from https://www.huffpost.com/highline/article/capitalist-takeover-college/

Castilla, E. J. (2008). Gender, race, and meritocracy in organizational careers. *American Journal of Sociology*, *113*(6), 1479–1526. https://doi.org/10.1086/588738

Castleman, B., & Goodman, J. (2018). Intensive college counseling and the enrollment and persistence of low-income students. *Education Finance and Policy*, *13*(1), 19–41. https://doi.org/10.1162/edfp_a_00204

Cellini, S. R., & Chaudhary, L. (forthcoming). Where do colleges advertise? Demographic targeting by u.s. colleges. *Economics of Education Review*.

Cheslock, J. J., & Kroc, R. (2012). Managing college enrollments. In R. Howard, B. Knight, & G. McLaughlin (Eds.), *The handbook for institutional researchers* (pp. 221–236). San Francisco, CA: Jossey-Bass.

Clinedinst, M. (2019). *State of college admission*. National Association for College Admission Counseling. Retrieved from https://www.nacacnet.org/state-of-college-admission-report/

College Board. (n.d.). College board search solutions. The College Board. Retrieved from https://cbsearch.collegeboard.org/solutions

College Board. (2011). *Segment Analysis Service: An educationally relevant geodemographic tagging service*. College Board. Retrieved from https://secure-media.collegeboard.org/mSSS/media/pdf/segment-analysis-service-overview.pdf

College Board. (2015). *PSAT/NMSQT: Understanding scores*. College Board. Retrieved from https://satsuite.collegeboard.org/media/pdf/2015-psat-nmsqt-concordance-tables.pdf

College Board. (2021). Introducing environmental attributes. *YouTube*. Retrieved from https://www.youtube.com/watch?v=VmTU9sb4ZiY

Cotter, K., Medeiros, M., Pak, C., & Thorson, K. (2021). "Reach the right people": The politics of "interests" in facebook's classification system for ad targeting. *Big Data & Society*, *8*(1), 16. https://doi.org/10.1177/2053951721996046

Cottom, T. M. (2017). *Lower ed: The troubling rise of for-profit colleges in the new economy*. New Press, The.

Cottom, T. M. (2020). Where platform capitalism and racial capitalism meet: The sociology of race and racism in the digital society. *Sociology of Race and Ethnicity*, *6*(4), 441–449. https://doi.org/10.1177/2332649220949473

Culliford, E. (2020). How political campaigns use your data: What campaigns know about U.S. Voters and how they use it to shape their strategies. *Reuters*. Retrieved from https://graphics.reuters.com/USA-ELECTION/DATA-VISUAL/yxmvjjgojvr/

Cunha, J. M., Miller, T., & Weisburst, E. (2018). Information and college decisions: Evidence from the texas GO center project. *Educational Evaluation and Policy Analysis*, *40*(1), 151–170. Journal Article. https://doi.org/10.3102/0162373717739349

Dache-Gerbino, A., Kiyama, J. M., & Sapp, V. T. (2018). The dangling carrot: Proprietary institutions and the mirage of college choice for Latina students. *The Review of Higher Education*, *42*(1), 29–60.

Doyle, W. R. (2010). Changes in institutional aid, 1992-2003: The evolving role of merit aid. *Research in Higher Education*, *51*(8), 789–810. Journal Article.

Duncan, O. D., Ohlin, L. E., Reiss, A. J., & Stanton, H. R. (1953). Formal devices for making selection decisions. *American Journal of Sociology*, *58*(6), 573–584. Retrieved from http://www.jstor.org/stable/2772558

Dynarski, S., Libassi, C., Michelmore, K., & Owen, S. (2021). Closing the gap: The effect of reducing complexity and uncertainty in college pricing on the choices of low-income students. *American Economic Review*, *111*(6), 1721–1756. https://doi.org/10.1257/aer.20200451

EAB. (2018). *Making your digital ads count: 15 lessons on new and emerging techniques in undergraduate recruitment marketing*. EAB.

EAB. (2019). The 5 key stages of college enrollment—and which metrics to track during each. Retrieved from https://eab.com/insights/daily-briefing/enrollment/the-5-key-stages-of-college-enrollment-and-which-metrics-to-track-during-each/

Equifax. (2023). Drive customer growth: Best practices for financial services firms to acquire the right customers and grow share. Retrieved from https://assets.equifax.com/marketing/US/assets/drive-customer-growth-ebook.pdf

Experian. (2023). *Mosaic: The best data powers the most robust segmentation*. Retrieved from https://www.experian.com/content/dam/marketing/na/assets/ems/marketing-services/documents/product-sheets/mosaic-product-sheet.pdf

Feathers, T. (2022). College prep software naviance is selling advertising access to millions of students. *The Markup*. Retrieved from https://graphics.reuters.com/USA-ELECTION/DATA-VISUAL/yxmvjjgojvr/https://themarkup.org/machine-learning/2022/01/13/college-prep-software-naviance-is-selling-advertising-access-to-millions-of-students

Federal Trade Commission. (2014). *Data brokers: A call for transparency and accountability*. Federal Trade Commission. Retrieved from https://www.ftc.gov/system/files/documents/reports/data-brokers-call-transparency-accountability-report-federal-trade-commission-may-2014/140527databrokerreport.pdf

Federal Trade Commission. (2016a). *Big data: A tool for inclusion or exclusion? Understanding the issues*. Federal Trade Commission. Retrieved from https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf

Federal Trade Commission. (2016b). *"Follow the lead" workshop*. Retrieved from http://www.ftc.gov/system/files/documents/reports/staff-perspective-follow-lead/staff_perspective_follow_the_lead_workshop.pdf

Fire Engine RED. (2022). *Data services: Search modeling*. Fire Engine RED. Retrieved from https://www.fire-engine-red.com/data-services/

Fourcade, M., & Healy, K. (2013). Classification situations: Life-chances in the neoliberal era. *Accounting Organizations and Society*, *38*(8), 559–572. Journal Article. https://doi.org/10.1016/j.aos.2013.11.002

Gewertz, C. (2019). *Which states require students to take the SAT or ACT? Which states require students to take the SAT or ACT? Which states require students to take the SAT or ACT?* Education Week. Retrieved from https://www.edweek.org/teaching-learning/which-states-require-students-to-take-the-sat-or-act

Green III, P. C., Baker, B. D., & Oluwole, J. O. (2021). School finance, race, and reparations.

Wash. And Lee Journal of Civil Rights and Social Justice, *27*(2), 484–558. Retrieved from https://scholarlycommons.law.wlu.edu/crsj/vol27/iss2/7/

Gurantz, O., Howell, J., Hurwitz, M., Larson, C., Pender, M., & White, B. (2021). A national-level informational experiment to promote enrollment in selective colleges. *Journal of Policy Analysis and Management*, *40*(2), 453–479. https://doi.org/https://doi.org/10.1002/pam.22262

Harcourt, B. E. (2007). *Against prediction: Profiling, policing, and punishing in an actuarial age* (pp. viii, 336 p.). Chicago: University of Chicago Press.

Harris, C. I. (1993). Whiteness as property. *Harvard Law Review*, *106*(8), 1707–1791. https://doi.org/10.2307/1341787

Hirschman, D., & Bosk, E. A. (2020). Standardizing biases: Selection devices and the quantification of race. *Sociology of Race and Ethnicity*, *6*(3), 348–364. https://doi.org/10.1177/2332649219844797

Holland, M. M. (2019). *Divergent paths to college: Race, class, and inequality in high schools*. Rutgers University Press. https://doi.org/10.36019/9780813590288

Hossler, D., & Bean, J. P. (1990). *The strategic management of college enrollments* (pp. xxii, 330 p.). Jossey-Bass.

Howell, J., Hurwitz, M. H., Mabel, Z., & Smith, J. (2021). *Participation in student search service is associated with higher college enrollment and completion*. College Board. Retrieved from https://cbsearch.collegeboard.org/pdf/college-outreach-and-student-outcomes.pdf

Hoxby, C. M. (1997). *How the changing market structure of u.s. Higher education explains college tuition* (No. Working Paper 6323). National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/W6323.pdf

Hoxby, C. M. (2009). The changing selectivity of american colleges. *Journal of Economic Perspectives*, *23*(4), 95–118. Retrieved from <Go to ISI>://000272677100005

Hoxby, C. M., & Avery, C. (2013). The missing "one-offs": The hidden supply of high merit students for highly selective colleges. *Brookings Papers on Economic Activity*, *2013*(1), 1–65. https://doi.org/10.1353/eca.2013.0000

Hurwitz, M. (2012). The impact of institutional grant aid on college choice. *Educational Evaluation and Policy Analysis*, *34*(3), 344–363. https://doi.org/10.3102/0162373712448957

Hyman, J. (2017). ACT for all: The effect of mandatory college entrance exams on postsecondary attainment and choice. *Education Finance and Policy*, *12*(3), 281–311. https://doi.org/10.1162/EDFP_a_00206

Jackson, B. A., & Reynolds, J. R. (2013). The price of opportunity: Race, student loan debt, and college achievement. *Sociological Inquiry*, *83*(3), 335–368. https://doi.org/10.1111/soin.12012

James Madison University. (2017). Commonwealth of virginia standard contract, contract no. UCPJMU4648.

Jaquette, O., & Salazar, K. G. (2022). *Student list policy: Problems, regulations, and a solution*. Washington, DC: TICAS. Retrieved from #

Jaquette, O., Salazar, K. G., & Martin, P. (2022). *The student list business: Primer and market dynamics*. washington, DC: TICAS. Retrieved from https://ticas.org/wp-content/uploads/2022/09/The-Student-List-Business_-Primer-and-Market-Dynamics.pdf

Jillson, E. (2021). *Aiming for truth, fairness, and equity in your company's use of AI.* Federal Trade Commission. Retrieved from https://www.ftc.gov/news-events/blogs/business-blog/2021/04/aiming-truth-fairness-equity-your-companys-use-ai

Khan, S. R. (2011). *Privilege: The making of an adolescent elite at st. Paul's school* (p. 232). Princeton, N.J.: Princeton University Press.

Killgore, L. (2009). Merit and competition in selective college admissions. *Review of Higher Education*, *32*(4), 469–488. Retrieved from <Go to ISI>://WOS:000266737500002

Kolluri, S. (2018). Advanced placement: The dual challenge of equal access and effectiveness. *Review of Educational Research*, *88*(5), 671–711. https://doi.org/10.3102/0034654318787268

Korver-Glenn, E. (2018). Compounding inequalities: How racial stereotypes and discrimination accumulate across the stages of housing exchange. *American Sociological Review*, *83*(4), 627–656. https://doi.org/10.1177/0003122418781774

Korver-Glenn, E. (2022). *Race brokers: Housing markets and racial segregation in 21st century urban america* (pp. pages cm). New York, NY: Oxford University Press.

Kraatz, M. S., Ventresca, M. J., & Deng, L. N. (2010). Precarious values and mundane innovations: Enrollment management in american liberal arts colleges. *Academy of Management Journal*, *53*(6), 1521–1545.

Kraus, M. W., Onyeador, I. N., Daumeyer, N. M., Rucker, J. M., & Richeson, J. A. (2019). The misperception of racial economic inequality. *Perspectives on Psychological Science*, *14*(6), 899–921. https://doi.org/10.1177/1745691619863049

Krippner, G. R., & Hirschman, D. (2022). The person of the category: The pricing of risk and the politics of classification in insurance and credit. *Theory and Society*, *51*(5), 685–727. https://doi.org/10.1007/s11186-022-09500-5

Lee, D. (2013). Household debt and credit: Student debt. Federal Reserve Bank of New York. Retrieved from https://www.newyorkfed.org/medialibrary/media/newsevents/mediaadvisory/2013/lee022813.pdf

Leeds, D. M., & DesJardins, S. L. (2015). The effect of merit aid on enrollment: A regression discontinuity analysis of iowa's national scholars award. *Research in Higher Education*, *56*(7), 471–495. https://doi.org/10.1007/s11162-014-9359-2

Leyshon, A., & Thrift, N. (1999). Lists come alive: Electronic systems of knowledge and the rise of credit-scoring in retail banking. *Economy and Society*, *28*(3), 434–466. https://doi.org/10.1080/03085149900000013

Long, B. T., & Kurlaender, M. (2009). Do community colleges provide a viable pathway to a baccalaureate degree? *Educational Evaluation and Policy Analysis*, *31*(1), 30–53. https://doi.org/10.3102/0162373708327756

Long, M. C. (2008). College quality and early adult outcomes. *Economics of Education Review*, *27*(5), 588–602. https://doi.org/10.1016/j.econedurev.2007.04.004

MacLeod, W. B., Riehl, E., Saavedra, J. E., & Urquiola, M. (2017). The big sort: College reputation and labor market outcomes. *American Economic Journal: Applied Economics*, *9*(3), 223–261. https://doi.org/10.1257/app.20160126

MacMilan, D., & Anderson, N. (2019). Student tracking, secret scores: How college admissions offices rank prospects before they apply. *Washington Post*, (October 14). Retrieved from https://www.washingtonpost.com/business/2019/10/14/colleges-quietly-rank-prospective-students-based-their-personal-data/

Marini, J. P., Young, L., & Shaw, E. J. (2021). *Re-examining the accuracy of self-reported high school grade point average (HSGPA)*. College Board. Retrieved from https://research.collegeboard.org/media/pdf/reexamining-accuracy-self-reported-high-school-gpa_0.pdf

McElhatton, N. (2004). Secrets of my success: Richard webber, founder of geodemographics. *Campaign Live UK*. Retrieved from https://www.campaignlive.co.uk/article/secrets-success-richard-webber-founder-geodemographics/226747

McPherson, M. S., & Schapiro, M. O. (1998). *The student aid game*. Princeton, NJ: Princeton University Press.

Melguizo, T. (2008). Quality matters: Assessing the impact of attending more selective institutions on college completion rates of minorities. *Research in Higher Education*, *49*(3), 214–236. https://doi.org/10.1007/s11162-007-9076-1

Moore, J. (2017). *Do students who opt into ACT's educational opportunity service (EOS) enroll in college at higher rates?* ACT, Inc. Retrieved from https://www.act.org/content/dam/act/unsecured/documents/R1652-benefits-of-act-eos-opt-in-2017-08.pdf

Mulhern, C. (2021). Changing college choices with personalized admissions information at scale: Evidence on naviance. *Journal of Labor Economics*, *39*(1), 219–262. https://doi.org/10.1086/708839

Napier, A., & Orrick, A. (2022). The economic, social, and political dimensions of platform studies in education. *Harvard Educational Review*, *92*(2), 206–208. https://doi.org/10.17763/1943-5045-92.2.206

Niu, S. X., & Tienda, M. (2010). Minority student academic performance under the uniform admission law: Evidence from the university of texas at austin. *Educational Evaluation and Policy Analysis*, *32*(1), 44–69. https://doi.org/10.3102/0162373709360063

Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. New York: New York University Press.

Norris, D. (2021). Embedding racism: City government credit ratings and the institutionalization of race in markets. *Social Problems*. https://doi.org/10.1093/socpro/spab066

Norris, D. (2022). The illusion of transparency: The political double standard in city credit ratings. *Socio-Economic Review*. Journal Article. https://doi.org/10.1093/ser/mwac016

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy* (First edition., pp. x, 259 pages). New York: Crown.

Odle, T. K., & Delaney, J. A. (2022). You are admitted! Early evidence on enrollment from idaho's direct admissions system. *Research in Higher Education*, *63*(6), 899–932. Journal Article. https://doi.org/10.1007/s11162-022-09675-x

Park, J. J., & Becks, A. H. (2015). Who benefits from SAT prep?: An examination of high school context and race/ethnicity. *Review of Higher Education*, *39*(1), 1–23. Retrieved from <Go to ISI>://WOS:000360777300001

Perrotta, C. (2021). Programming the platform university: Learning analytics and predictive infrastructures in higher education. *Research in Education*, *109*(1), 53–71. https://doi.org/10.1177/0034523720965623

Poon, M. (2007). Scorecards as devices for consumer credit: The case of fair, isaac & company incorporated. *Sociological Review*, *55*, 284–306. https://doi.org/10.1111/j.1467-954X.2007.00740.x

Posecznick, A. (2017). *Selling hope and college merit, markets, and recruitment in an unranked school*. Ithaca ; London: Cornell University Press. Retrieved from https:

//muse.jhu.edu/book/52616
Posselt, J. R. (2016). *Inside graduate admissions: Merit, diversity, and faculty gatekeeping* (pp. x, 250 pages). Cambridge, MA: Harvard University Press.
Posselt, J. R., Jaquette, O., Bielby, R., & Bastedo, M. N. (2012). Access without equity: Longitudinal analyses of institutional stratification by race and ethnicity, 1972-2004. *American Educational Research Journal*, *49*(6), 1074–1111.
Quirk, M. (2005). The best class money can buy: The rise of the "enrollment manager" and the cutthroat quest for competitive advantage. The secret weapen: Finacial-aid leveraging. *The Atlantic*, (November). Retrieved from https://www.theatlantic.com/magazine/archive/2005/11/the-best-class-money-can-buy/304307/
Reardon, S. F., Kalogrides, D., & Shores, K. (2019). The geography of racial/ethnic test score gaps. *American Journal of Sociology*, *124*(4), 1164–1221. https://doi.org/10.1086/700678
Reber, S., & Smith, E. (2023). College enrollment disparities: Understanding the role of academic preperation. *The Brookings Institution*. Retrieved from https://www.brookings.edu/research/college-enrollment-disparities/
Rivard, R. (2013). Political campaignstyle targeting comes to student search. *InsideHigherEd*, (Oct 24). Magazine Article. Retrieved from https://www.insidehighered.com/news/2013/10/24/political-campaign-style-targeting-comes-student-search?width=775&height=500&iframe=true
Rodriguez, A., & Hernandez-Hamed, E. (2020). Understanding unfulfilled AP potential across the participation pipeline by race and income. *Teachers College Record*, *122*(9), 38. Retrieved from <Go to ISI>://WOS:000595649100009
Rodriguez, A., & McGuire, K. M. (2019). More casses, more acess? Understanding the effects of course offerings on back-white gaps in advanced placement course-taking. *Review of Higher Education*, *42*(2), 641–679. Retrieved from <Go to ISI>://WOS:000454537100016
Rothstein, R. (2017). *The color of law: A forgotten history of how our government segregated America*. Liveright Publishing.
Ruffalo Noel Levitz. (2018). *2018 marketing and student recruitment report of effective practices*. Ruffalo Noel Levitz. Retrieved from http://learn.ruffalonl.com/rs/395-EOG-977/images/RNL_2018_Student_Recruitment_Marketing_Report_EM-19.pdf
Ruffalo Noel Levitz. (2021). RNL student search and engagement. Retrieved from https://www.ruffalonl.com/enrollment-management-solutions/building-demand/student-search-and-engagement/
Ruffalo Noel-Levitz. (2022a). *2022 cost of recruiting an undergraduate student report*. Ruffalo Noel-Levitz. Retrieved from https://www.ruffalonl.com/thank-you/download-the-2022-cost-of-recruiting-an-undergraduate-student-report/
Ruffalo Noel-Levitz. (2022b). *2022 marketing and recruitment practices for undergraduate students report*. Ruffalo Noel-Levitz. Retrieved from https://www.ruffalonl.com/papers-research-higher-education-fundraising/marketing-and-recruitment-practices-for-undergraduate-students/
Ruffalo Noel-Levitz. (2022c). *2022 online program marketing and recruitment practices*. Ruffalo Noel-Levitz. Retrieved from https://www.ruffalonl.com/thank-you/download-the-2022-online-marketing-and-recruitment-practices-report/
Salazar, K. G. (2022). Recruitment redlining by public research universities in the los angeles and dallas metropolitan areas. *The Journal of Higher Education*, 1–37. https:

//doi.org/10.1080/00221546.2021.2004811

Salazar, K. G., Jaquette, O., & Han, C. (2021). Coming soon to a neighborhood near you? Off-campus recruiting by public research universities. *American Educational Research Journal*, *58*(6), 1270–1314. https://doi.org/10.3102/00028312211001810

Salazar, K. G., Jaquette, O., & Han, C. (2022). *Geodemographics of student list purchases: A first look*. Washington, DC: TICAS. Retrieved from https://ticas.org/wp-content/uploads/2022/09/Geodemographics-of-Student-List-Purchases_A-First-Look.pdf

Schmidt, D. (2019). *Prospect search filters*. Encoura. Retrieved from https://helpcenter.encoura.org/hc/en-us/articles/360035260452-Prospect-Search-Filters-

Schmidt, D. (2022). *Prospect search filters*. Encoura. Retrieved from https://helpcenter.encoura.org/hc/en-us/articles/360035260452-Prospect-Search-Filters-

Shamsuddin, S. (2016). Berkeley or bust? Estimating the causal effect of college selectivity on bachelor's degree completion. *Research in Higher Education*, *57*(7), 795–822. https://doi.org/10.1007/s11162-016-9408-0

Singer, P. (1988). Behind The Flood of Mail: Name Brokers. *The New York Times*. Retrieved from https://www.nytimes.com/1988/01/24/nyregion/behind-the-flood-of-mail-name-brokers.html

Smith, J., Howell, J., & Hurwitz, M. (2022). The impact of college outreach on high schoolers' college choices: Results from over one thousand natural experiments. *Education Finance and Policy*, *17*(1), 105–128. https://doi.org/10.1162/edfp_a_00334

Stevens, M. L. (2007). *Creating a class: College admissions and the education of elites* (p. 308). Cambridge, MA: Harvard University Press.

Tiako, M. J. N., South, E., & Ray, V. (2021). Medical schools as racialized organizations: A primer. *Annals of Internal Medicine*, *174*(8), 1143–1144. https://doi.org/10.7326/m21-0369 %m 34058105

Tough, P. (2019). What college admissions officers really want. *New York Times Magazine*, (Sept. 10). Retrieved from https://www.nytimes.com/interactive/2019/09/10/magazine/college-admissions-paul-tough.html

US Department of Education. (2023a). *Requirements and responsibilities for third-party servicers and institutions*. US Department of Education. Retrieved from https://fsapartners.ed.gov/knowledge-center/library/dear-colleague-letters/2023-02-15/requirements-and-responsibilities-third-party-servicers-and-institutions-updated-feb-28-2023

US Department of Education. (2023b). *Update on the department of education's third-party servicer guidance*. US Department of Education. Retrieved from https://blog.ed.gov/2023/04/update-on-the-department-of-educations-third-party-servicer-guidance/

Viano, S., & Baker, D. J. (2020). How administrative data collection and analysis can better reflect racial and ethnic identities. *Review of Research in Education*, *44*(1), 301–331. https://doi.org/10.3102/0091732X20903321

Waxman, B. (2019). The power of list segmentation part i: Are you already doing this? *intead, Global & Local Academic Branding*. Retrieved from https://services.intead.com/blog/the-power-of-list-segmentation-part-i-are-you-already-doing-this

Webber, R. (1988). Exploiting marketing opportunities. *Credit Management*, 36–37.

Winston, G. C. (1999). Subsidies, hierarchy and peers: The awkward economics of higher education. *Journal of Economic Perspectives*, *13*(1), 13–36. Retrieved from <Go to ISI>://000078904300002

8 Tables

Table 1: Top filter combinations used in College Board orders purchased purchased by research vs. ma/doctoral

Research			MA/doctoral		
Filters	**Count**	**Percent**	**Filters**	**Count**	**Percent**
HS grad class, GPA, SAT, Zip code	99	19%	HS grad class, GPA, PSAT, Zip code	143	44%
HS grad class, GPA, SAT, PSAT, Rank, State, Race	39	8%	HS grad class, GPA, SAT, Zip code	107	33%
HS grad class, SAT, State	38	7%	HS grad class, GPA, SAT, PSAT, Zip code	28	9%
HS grad class, PSAT, State	28	6%	HS grad class, GPA, SAT, State	7	2%
HS grad class, GPA, PSAT, State, Race	20	4%	HS grad class, SAT, Geomarket	6	2%
HS grad class, PSAT, State, Low SES	20	4%	HS grad class, GPA, SAT, County	5	2%
HS grad class, GPA, PSAT, State	17	3%	HS grad class, GPA, SAT, PSAT, County	4	1%
HS grad class, GPA, SAT, State	16	3%	HS grad class, GPA, PSAT, State	2	1%
HS grad class, GPA, AP score, Geomarket	15	3%	HS grad class, SAT, Geomarket, College type	2	1%
HS grad class, GPA, SAT, PSAT, State, Segment, Gender	13	3%	HS grad class, SAT, County, College location	2	1%

Notes: Top filter combinations are based on 830 College Board student list purchases made by research (N=8) and ma/doctoral (N=6) universities from 2016-2020. Geodemographic and Segment filters are proprietary filters created by College Board that use geodemography to predict the college-going behaviors of students within specific geographic areas.

Table 2: HSLS09 Descriptive Statistics

	Unweighted	**N**	**SE**	**Pct**
Race/Ethnicity				
White	9,390	2,163,043	45,293	51.7
Asian	1,370	150,222	15,373	3.6
Hisp	2,520	920,384	41,451	22.0
Black	1,660	574,370	36,346	13.7
Multi	1,410	332,043	12,921	7.9
NH/PI	70	18,784	5,241	0.4
AI/AN	110	28,519	6,288	0.7
Academic Filters				
College Entrance Exam Completer	7,910	1,860,677	54,277	55.6
College Entrance Exam Non-Completer	8,610	2,326,689	54,249	44.4
College Pre-Entrance Exam Completer	4,780	3,086,739	51,247	73.7
College Pre-Entrance Exam Non-Completer	11,760	1,100,627	51,417	26.3
AP test-taker (any)	2,990	694,359	33,918	16.6
AP non-test-taker (any)	13,530	3,493,007	34,022	83.4
AP test-taker (STEM)	1,800	383,669	23,721	9.2
AP non-test-taker (STEM)	14,720	3,803,697	23,893	90.8
Academic GPA	16,480	4,177,402	6,863	99.8
Missing Academic GPA	40	9,964	6,562	0.2

* Unweighted sample sizes rounded to nearest 10 per NCES restricted data license regulations

9 Figures

Figure 1: The Enrollment Funnel

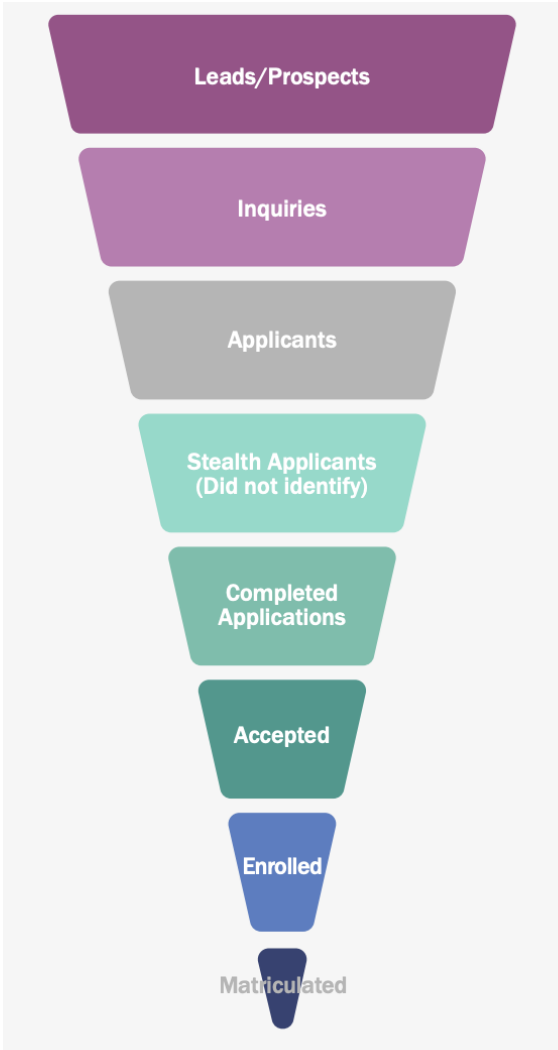


Figure 2: Test Takers Across College Extrance, College Pre-Entrance, and AP Assessments

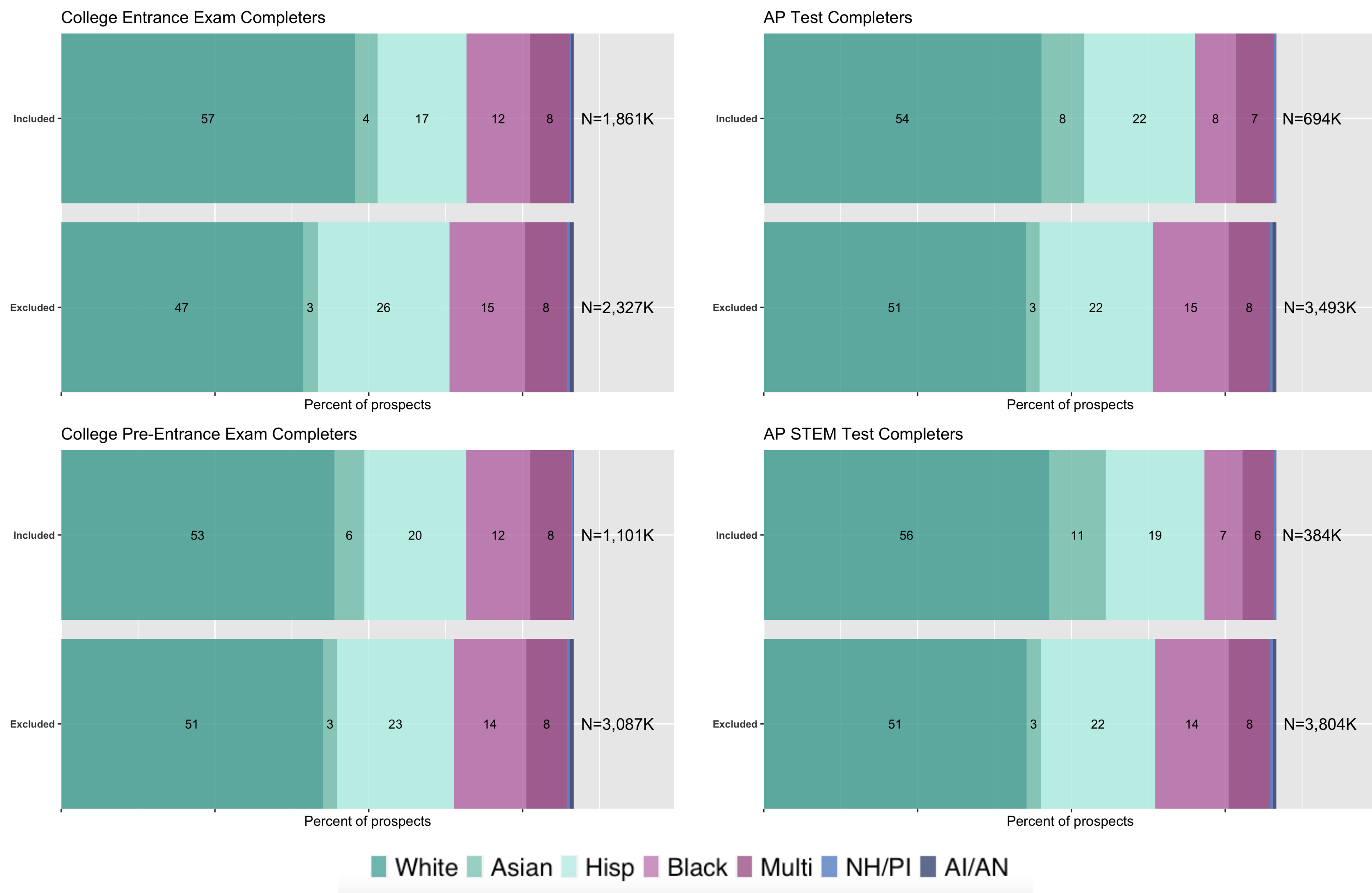


Figure 3: College Entrance and Pre-Entrance Exam Filters Across Thresholds

Figure 4: AP Filter Across Thresholds

Figure 5: Zip Code Filter Across Affluence Percentiles

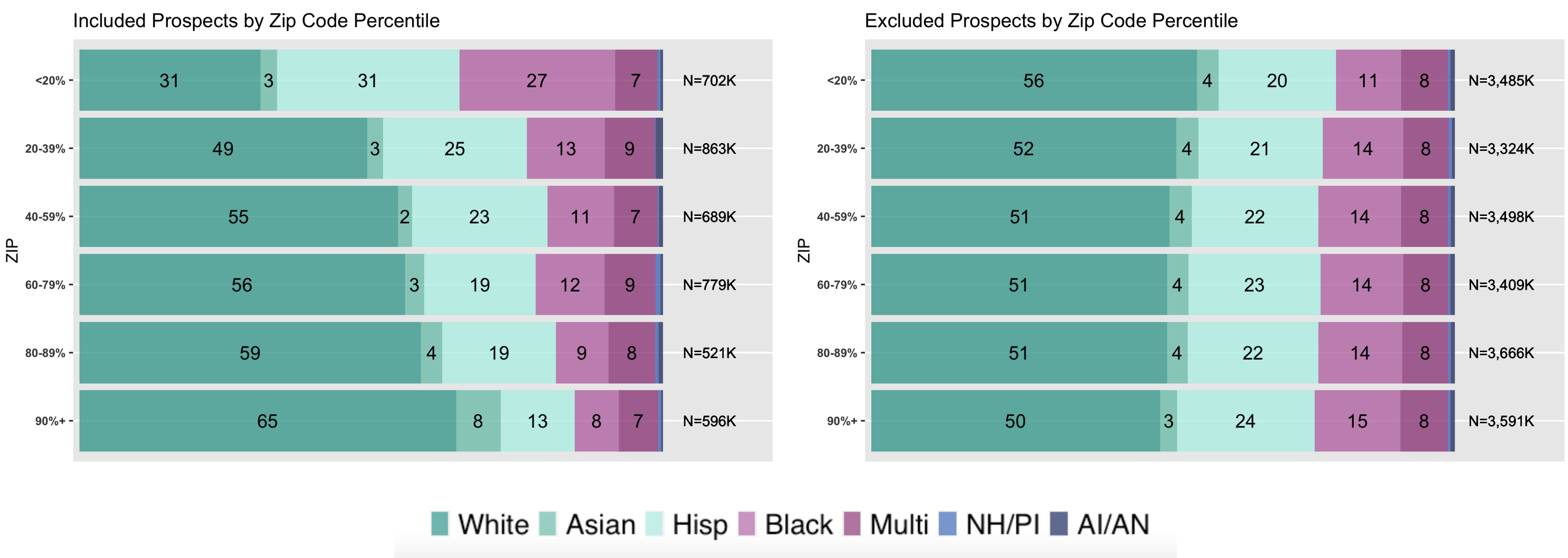


Figure 6: Filters used in College Board Orders Purchased by 14 Public Universities

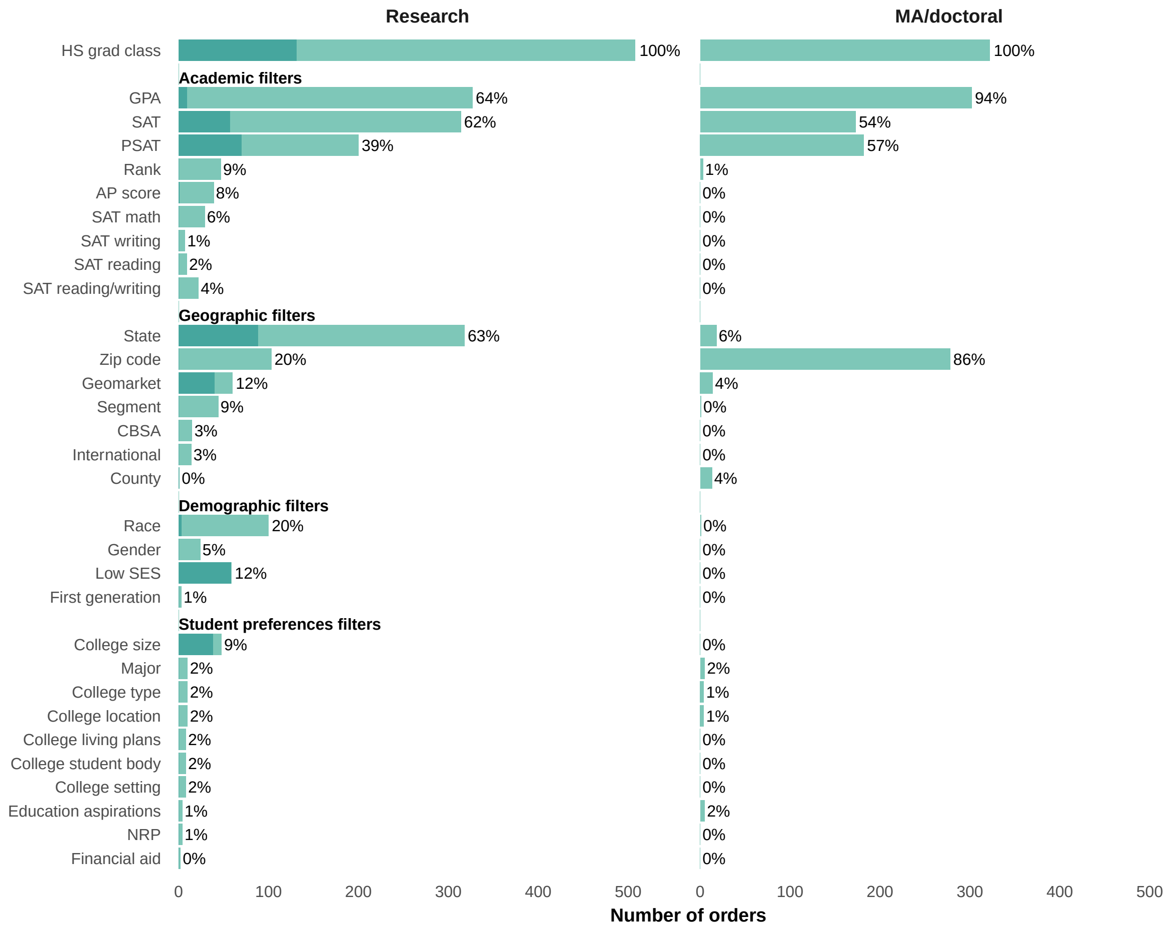


Figure 7: SAT Filter Used by Research vs. MA/Doctoral Public Universities

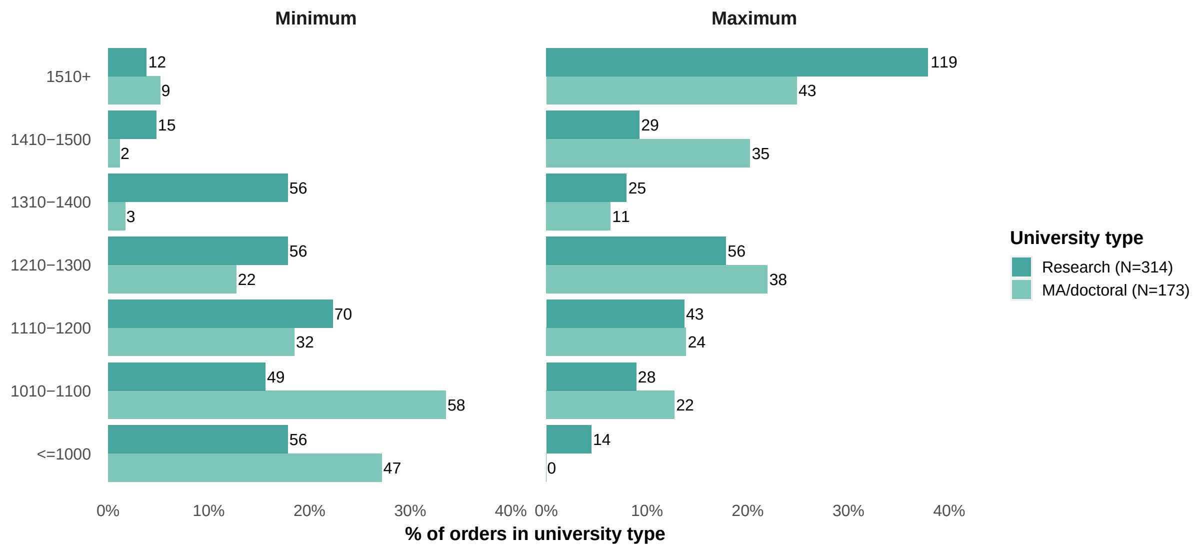


Figure 8: PSAT Filter Used by Research vs. MA/Doctoral Universities

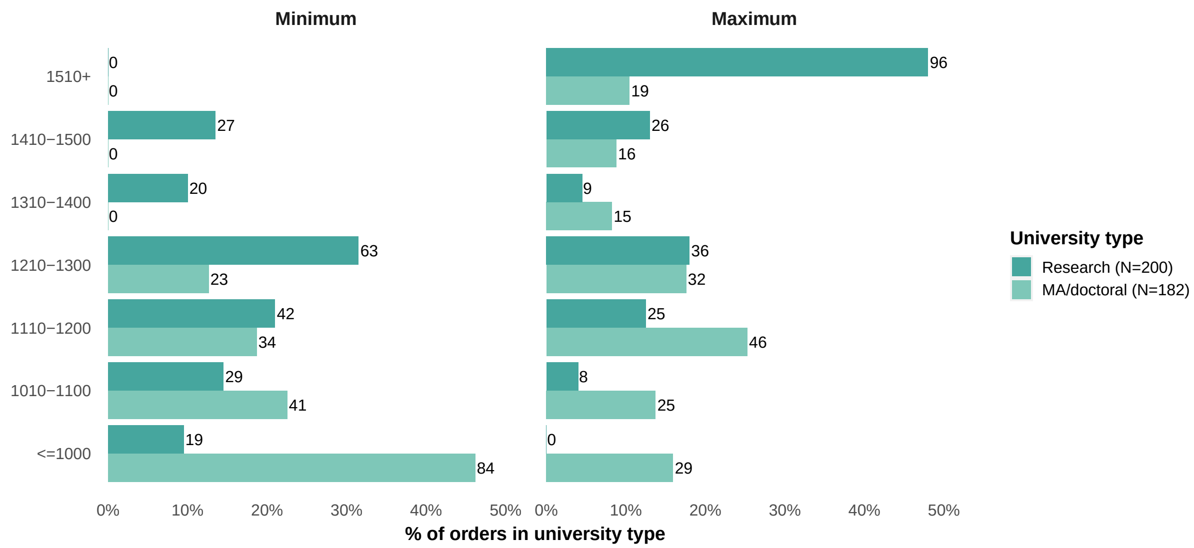


Figure 9: Academic Combinations: GPA (3.0+) and College Entrance or Pre-Entrance Exams (across score thresholds)

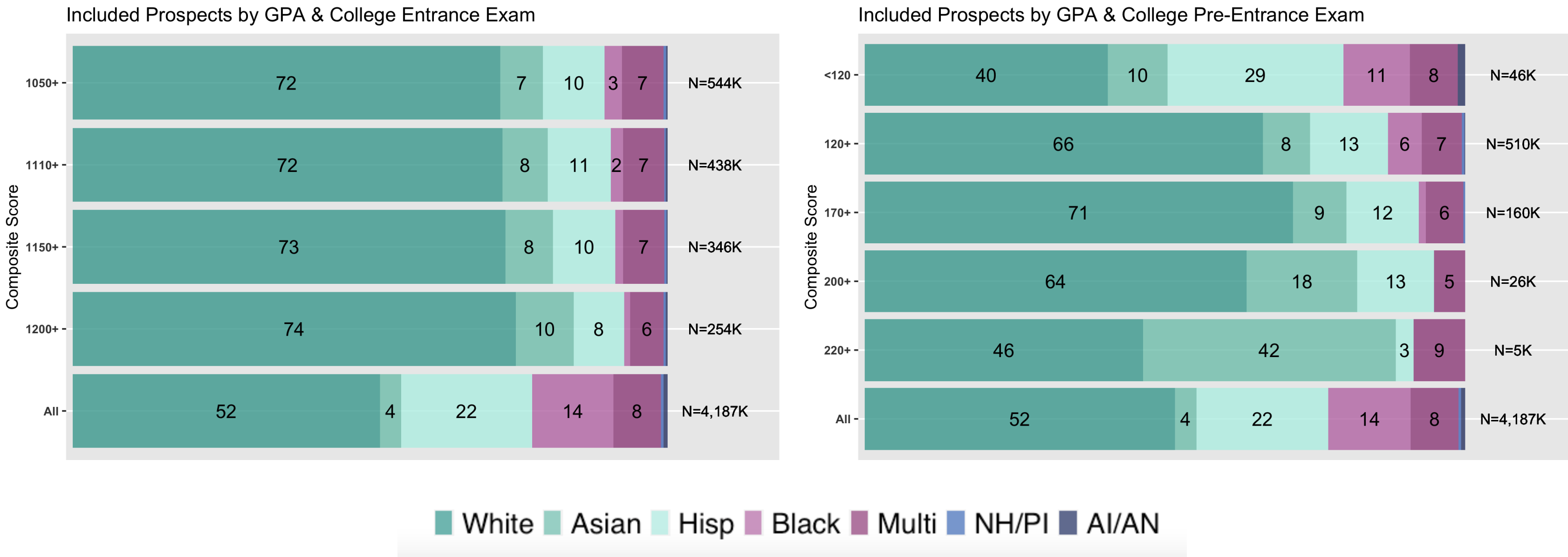


Figure 10: Academic and Geographic Combination: GPA (3.0+), College Pre-Entrance (150+) or Entrance (1050+) Exams, and Zip (across income thresholds)

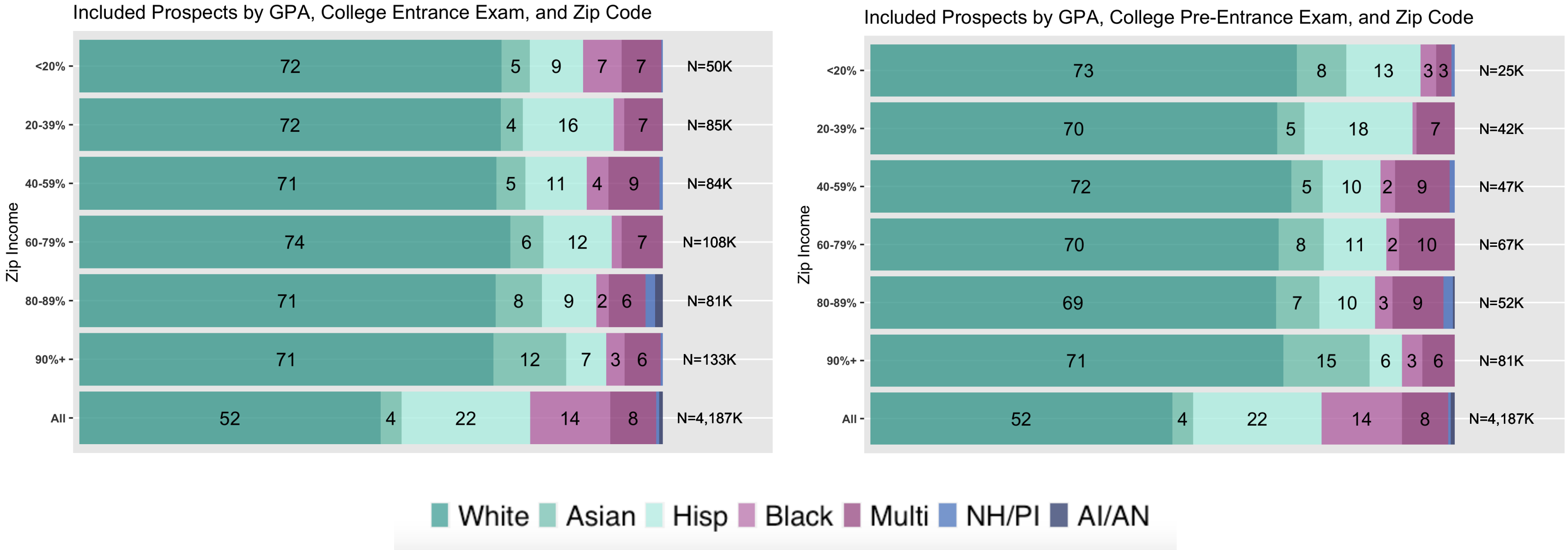
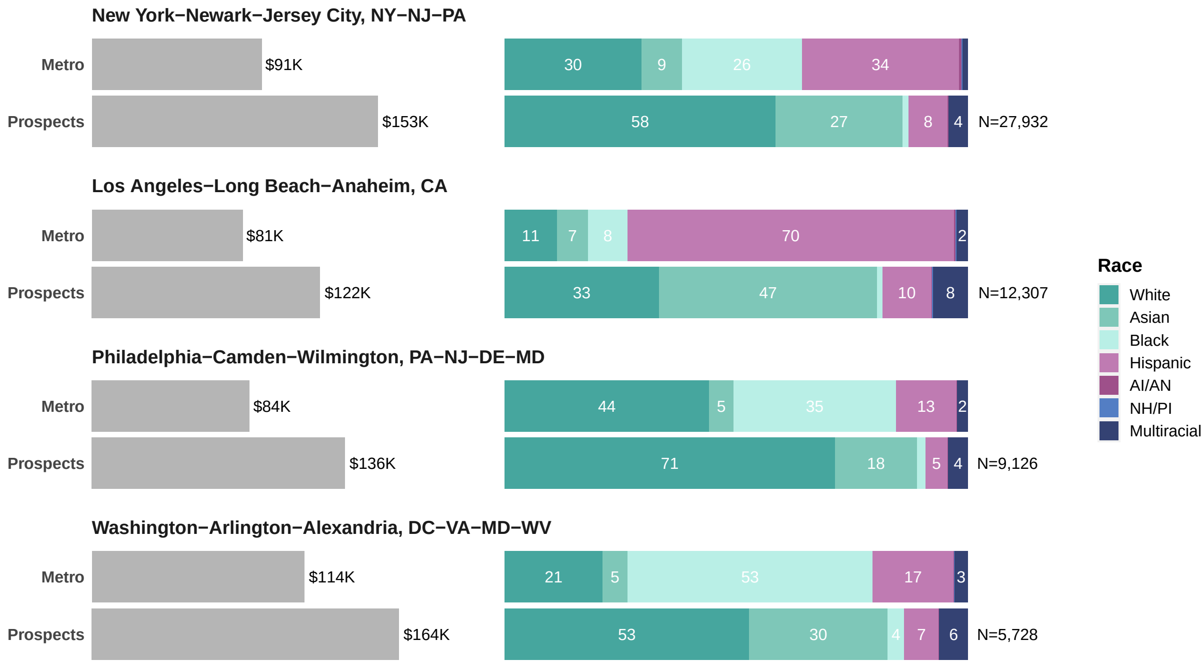


Figure 11: Segment Filter Prospects by Metropolitan Area



Note: Filters used across these orders include HS Class, GPA (B-A+), State (in-state vs. out-of-state), AP STEM (3 min for in-state; 4 min for out-of-state) or SAT (1200 minimum for in-state; 1300 minimum for out-of-state) with STEM major interest

Figure 12: Maps of Segment Filter Prospects by Metropolitan Area

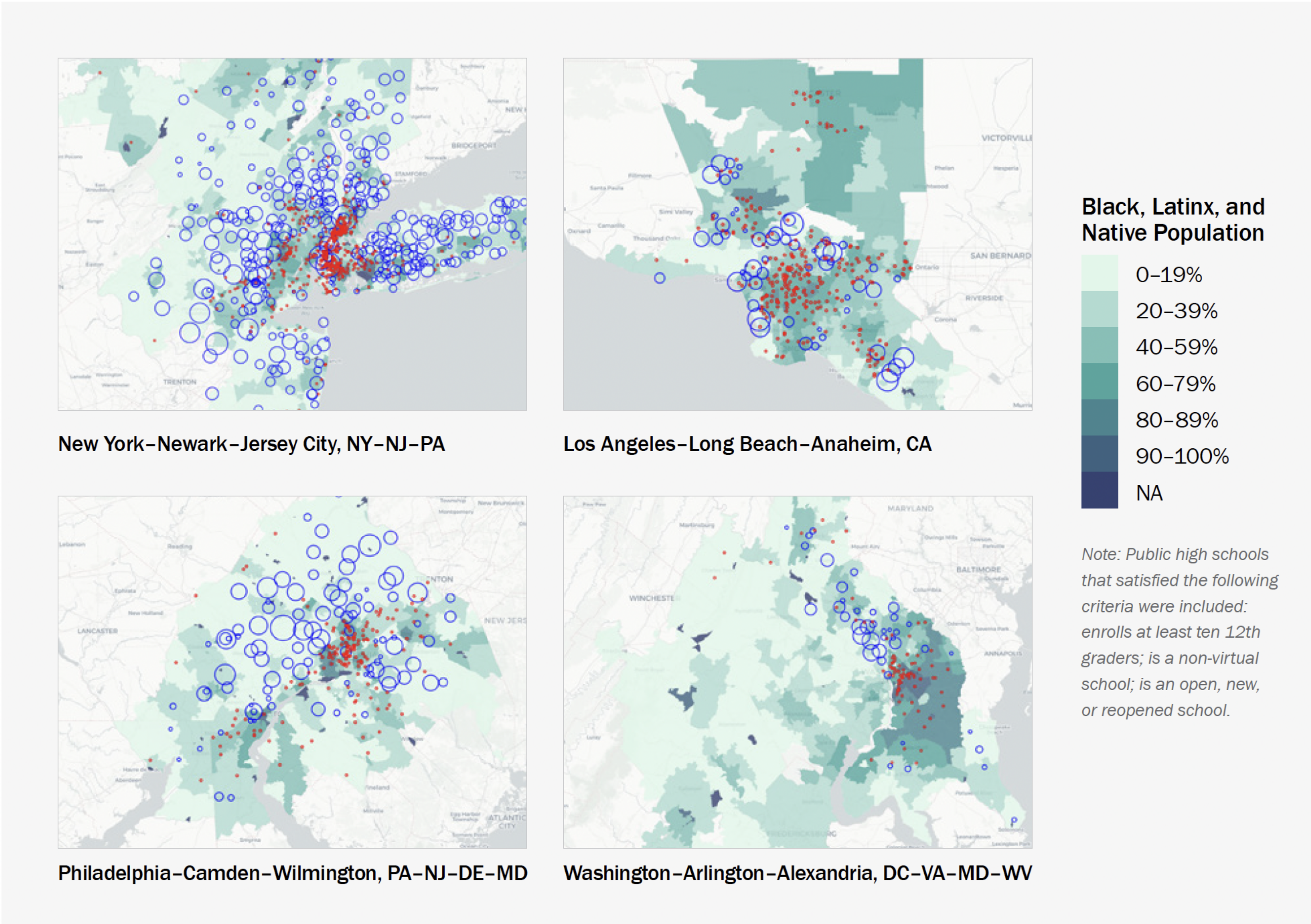
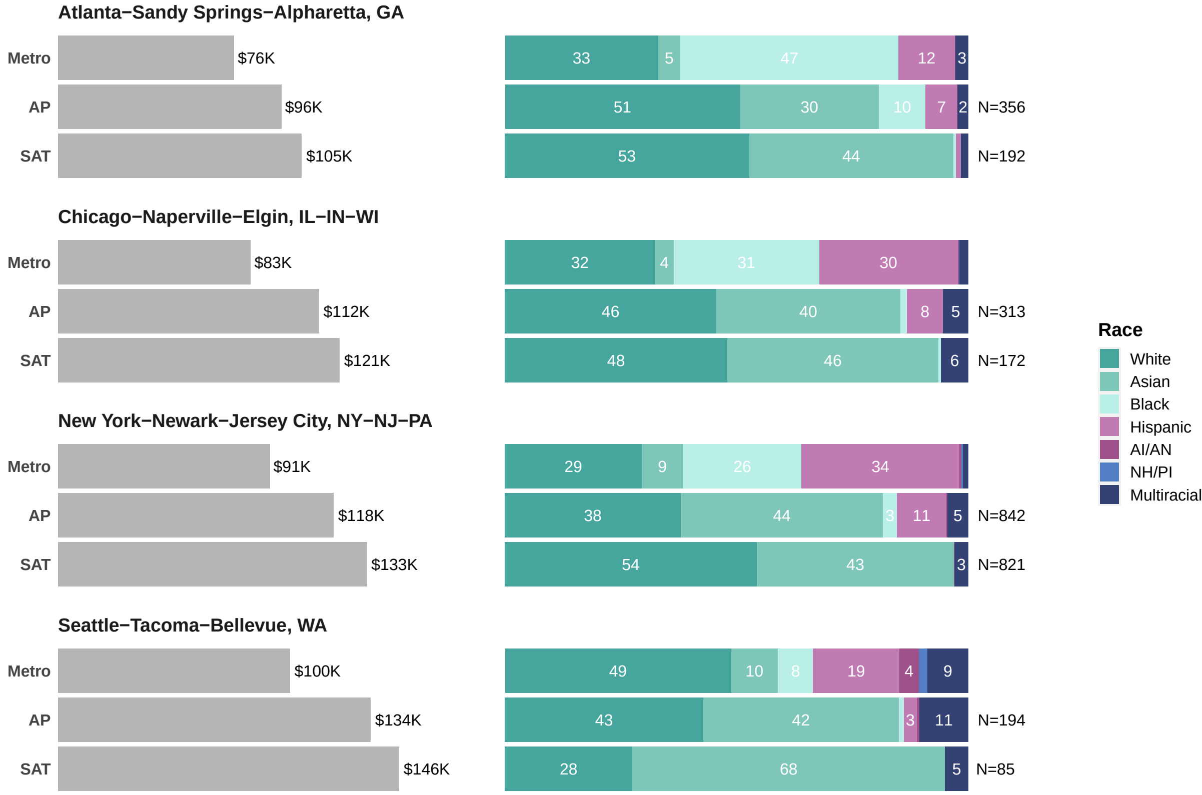


Figure 13: Women in STEM Prospects by Metropolitan Area



Note: Filters used across these orders include HS Class, Segment, GPA (B-A+), PSAT/SAT (1220-1450); State/CBSAs

10 Online Appendix

Table 3: Assessment Completer Differences in Proportion

	Included	Excluded	Difference	Lower CI	Upper CI
College Entrance Exam					
White	0.573	0.472	0.101***	0.100	0.102
Asian	0.045	0.029	0.016***	0.015	0.016
Hisp	0.173	0.257	-0.084***	-0.085	-0.083
Black	0.124	0.147	-0.023***	-0.024	-0.022
Multi	0.077	0.081	-0.004***	-0.005	-0.004
NH/PI	0.003	0.006	-0.003***	-0.003	-0.002
AI/AN	0.005	0.008	-0.003***	-0.003	-0.003
College Pre-Entrance Exam					
White	0.533	0.511	0.022***	0.021	0.023
Asian	0.058	0.028	0.030***	0.030	0.031
Hisp	0.199	0.227	-0.028***	-0.029	-0.027
Black	0.125	0.142	-0.017***	-0.018	-0.016
Multi	0.08	0.079	0.001***	0.001	0.002
NH/PI	0.003	0.005	-0.002***	-0.002	-0.002
AI/AN	0.002	0.009	-0.007***	-0.007	-0.007
AP					
White	0.542	0.512	0.030***	0.029	0.031
Asian	0.083	0.026	0.057***	0.056	0.058
Hisp	0.216	0.221	-0.005***	-0.006	-0.004
Black	0.081	0.148	-0.067***	-0.068	-0.067
Multi	0.072	0.081	-0.009***	-0.009	-0.008
NH/PI	0.005	0.004	0.001***	0.000	0.001
AI/AN	0.001	0.008	-0.007***	-0.007	-0.006
AP STEM					
White	0.557	0.513	0.044***	0.043	0.046
Asian	0.11	0.028	0.082***	0.081	0.083
Hisp	0.193	0.223	-0.030***	-0.031	-0.029
Black	0.074	0.144	-0.070***	-0.071	-0.069
Multi	0.06	0.081	-0.021***	-0.022	-0.020
NH/PI	0.004	0.005	-0.001	-0.000	0.000
AI/AN	0.002	0.007	-0.005***	-0.006	-0.005

Note: *p<0.05, **p<0.01, ***p<0.001

Figure 14: Academic and Geographic Combination: GPA (3.0+) and AP (across score thresholds)

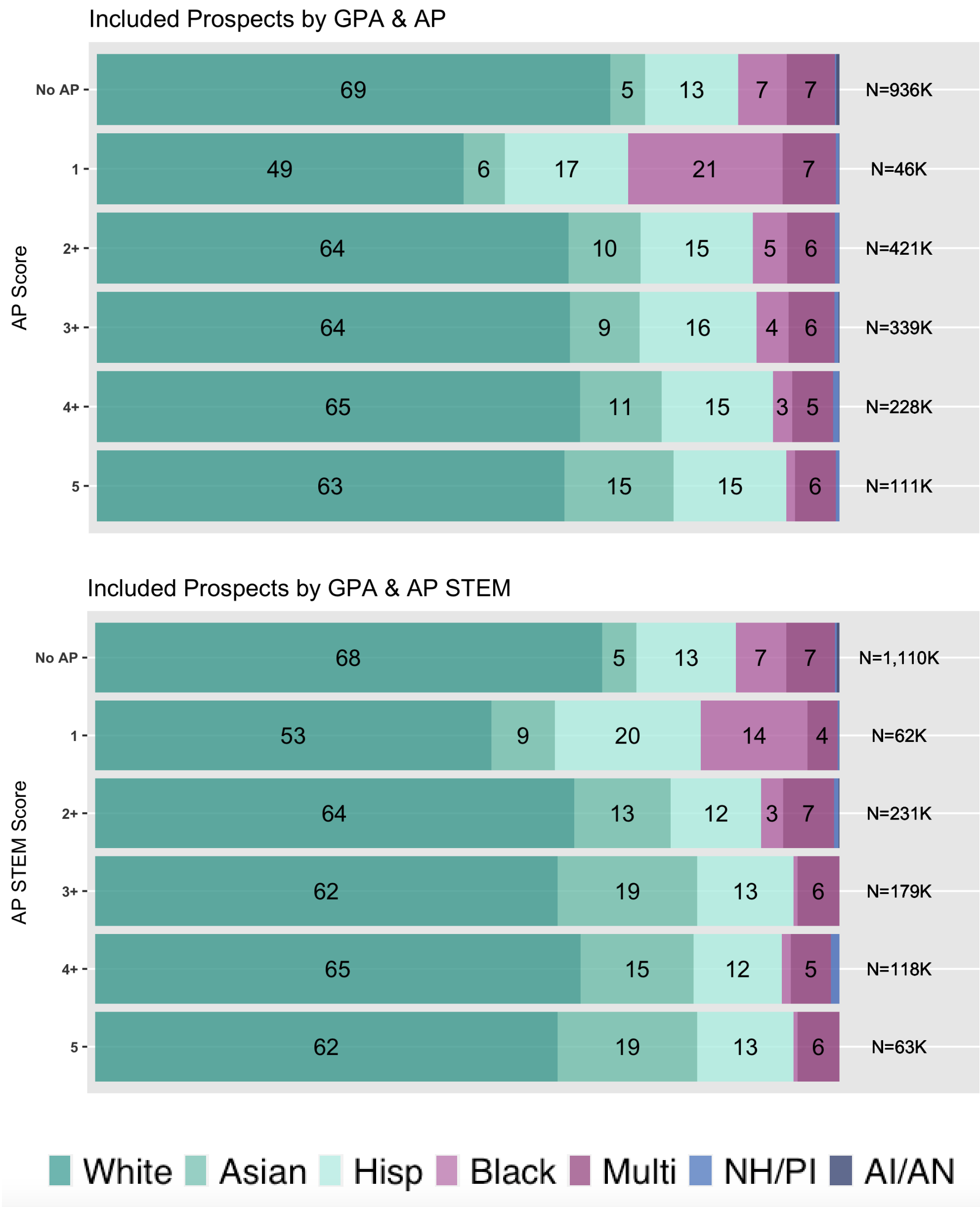


Table 4: Score Threshold Proportion Differences in Included vs. Excluded across Race/Ethnicity

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
College Entrance Exam							
Less than 1000	-0.062***	-0.010***	0.004***	0.065***	0.005***	-0.003***	0.002***
1000+	0.217***	0.033***	-0.129***	-0.103***	-0.012***	-0.001***	-0.006***
1200+	0.209***	0.057***	-0.137***	-0.103***	-0.025***	0.001***	-0.003***
1300+	0.205***	0.090***	-0.137***	-0.122***	-0.027***	-0.002***	NA
1400+	0.170***	0.160***	-0.175***	-0.130***	-0.012***	NA	NA
College Pre-Entrance Exam							
Less than 120	-0.194***	0.007***	0.076***	0.105***	0.014***	-0.004***	-0.005***
120+	0.098***	0.034***	-0.062***	-0.060***	-0.003***	-0.001***	-0.006***
170+	0.185***	0.051***	-0.093***	-0.123***	-0.015***	0.001*	NA
200+	0.116***	0.151***	-0.102***	NA	-0.015***	NA	NA
220+	-0.078***	0.417***	-0.191***	NA	0.002	NA	NA
AP							
1	-0.143***	0.022***	0.056***	0.077***	-0.001	-0.003***	-0.006***
2+	0.066***	0.061***	-0.017***	-0.094***	-0.010***	0.001***	-0.007***
3+	0.070***	0.058***	-0.017***	-0.091***	-0.015***	0.001*	-0.005***
4+	0.086***	0.071***	-0.022***	-0.106***	-0.026***	0.003***	-0.005***
5+	0.084***	0.104***	-0.046***	-0.109***	-0.025***	0.001	NA
AP STEM							
1	-0.100***	0.046***	0.090***	0.015***	-0.040***	-0.004***	-0.007***
2+	0.101***	0.092***	-0.077***	-0.101***	-0.012***	0.002***	-0.005***
3+	0.130***	0.105***	-0.097***	-0.111***	-0.025***	0.003***	-0.005***
4+	0.113***	0.119***	-0.106***	-0.103***	-0.023***	0.007***	-0.006***
5+	0.078***	0.151***	-0.101***	-0.096***	-0.020***	NA	NA
GPA							
Less than 2.0	-0.198***	-0.036***	0.104***	0.109***	0.016***	-0.002***	0.006***
2.0+	0.193***	0.037***	-0.103***	-0.107***	-0.016***	0.002***	-0.006***
2.5+	0.212***	0.037***	-0.112***	-0.112***	-0.018***	-0.001***	-0.006***
3.0+	0.109***	0.032***	-0.068***	-0.060***	-0.008***	-0.004***	-0.002***
3.5+	0.233***	0.034***	-0.124***	-0.112***	-0.026***	0.000	-0.006***

*Note: *p<0.05, **p<0.01, ***p<0.001*

Table 5: Zip Code Affluence Proportion Differences in Included vs. Excluded across Race/Ethnicity

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
Affluence Percentile							
Less than 20%	-0.248***	-0.009***	0.112***	0.156***	-0.008***	0.001***	-0.003***
20-39%	-0.030***	-0.011***	0.034***	-0.005***	0.008***	-0.004***	0.008***
40-59%	0.035***	-0.014***	0.015***	-0.028***	-0.005***	-0.002***	0.000
60-79%	0.051***	-0.004***	-0.035***	-0.024***	0.011***	0.004***	-0.003***
80-89%	0.079***	0.000*	-0.028***	-0.054***	0.001*	0.002***	0.000***
Greater than 90%	0.151***	0.047***	-0.108***	-0.071***	-0.013***	0.001***	-0.004***

*Note: *p<0.05, **p<0.01, ***p<0.001*

Table 6: GPA and College Entrance or Pre-Entrance Exam Score Threshold Proportion Differences in Included vs. Excluded across Race/Ethnicity

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
College Entrance Exam							
1050+	0.233***	0.041***	-0.133***	-0.124***	-0.011***	0.001	-0.006***
1100+	0.229***	0.045***	-0.127***	-0.130***	-0.011***	-0.002***	-0.004***
1150+	0.229***	0.048***	-0.126***	-0.135***	-0.010***	-0.002***	-0.005***
College Pre-Entrance Exam							
1200+	0.243***	0.066***	-0.144***	-0.135***	-0.025***	-0.001***	-0.004***
<120	-0.135***	0.075***	0.081***	-0.012***	0.003*	NA	-0.006***
120+	0.164***	0.051***	-0.099***	-0.097***	-0.012***	-0.001***	-0.005***
170+	0.199***	0.059***	-0.098***	-0.130***	-0.021***	-0.002***	NA
200+	0.119***	0.154***	-0.089***	NA	-0.033***	NA	NA
220+	-0.053***	0.386***	-0.190***	NA	0.007	NA	NA

Note: *p<0.05, **p<0.01, ***p<0.001

Table 7: GPA, College Entrance/Pre-Entrance Exam, and Zip Code Proportion Differences in Included vs. Excluded across Race/Ethnicity

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
College Entrance Exam (1050+)							
Less than 20%	0.210***	0.012***	-0.129***	-0.072***	-0.011***	-0.002***	-0.007***
20-39%	0.210***	0.001*	-0.065***	-0.122***	-0.015***	-0.005***	-0.006***
40-59%	0.201***	0.014***	-0.117***	-0.102***	0.009***	0.002***	-0.007***
60-79%	0.228***	0.021***	-0.106***	-0.123***	-0.009***	-0.005***	-0.007***
80-89%	0.200***	0.044***	-0.129***	-0.117***	-0.017***	0.012***	0.006***
Greater than 90%	0.200***	0.091***	-0.156***	-0.110***	-0.019***	0.000	NA
College Pre-Entrance Exam (150+)							
Less than 20%	0.215***	0.049***	-0.093***	-0.111***	-0.054***	0.002**	-0.007***
20-39%	0.181***	0.011***	-0.036***	-0.131***	-0.014***	-0.005***	-0.007***
40-59%	0.206***	0.017***	-0.122***	-0.113***	0.014***	0.005***	-0.007***
60-79%	0.184***	0.042***	-0.115***	-0.118***	0.017***	-0.005***	-0.007***
80-89%	0.180***	0.039***	-0.125***	-0.109***	0.008***	0.012***	-0.004***
Greater than 90%	0.193***	0.114***	-0.167***	-0.104***	-0.024***	NA	NA

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

Table 8: GPA and AP Proportion Differences in Included vs. Excluded across Race/Ethnicity

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
AP							
1	-0.023***	0.020***	-0.054***	0.072***	-0.007***	0.000	-0.006***
2+	0.132***	0.068***	-0.077***	-0.100***	-0.017***	0.001***	-0.006***
3+	0.131***	0.063***	-0.068***	-0.102***	-0.019***	0.002***	-0.006***
4+	0.141***	0.078***	-0.074***	-0.118***	-0.026***	0.004***	-0.006***
5+	0.116***	0.114***	-0.070***	-0.130***	-0.025***	0.001***	NA
AP STEM							
1	0.016***	0.050***	-0.024***	0.006***	-0.039***	-0.003***	-0.006***
2+	0.134***	0.100***	-0.104***	-0.113***	-0.012***	0.002***	-0.006***
3+	0.163***	0.108***	-0.114***	-0.129***	-0.025***	0.004***	NA
4+	0.139***	0.119***	-0.105***	-0.129***	-0.026***	0.008***	NA
5+	0.106***	0.153***	-0.091***	-0.134***	-0.024***	NA	NA

*Note: *p<0.05, **p<0.01, ***p<0.001*

Table 9: Filter by neighborhood segments

2011 D+ Cluster	SAT Math	SAT CR	Going Out of State	Percent NonWhite	Need Financial Aid	Med Income
51	546	533	32%	30%	57%	$95,432
52	480	470	30%	58%	71%	$63,578
53	561	544	32%	50%	55%	$92,581
54	458	443	25%	83%	76%	$38,977
55	566	565	52%	24%	63%	$71,576
56	420	411	29%	93%	66%	$35,308
57	541	519	52%	47%	43%	$67,394
58	533	489	28%	87%	69%	$68,213
59	561	562	52%	24%	74%	$54,750
60	589	590	63%	37%	36%	$104,174
61	585	567	51%	30%	40%	$123,858
62	596	595	67%	24%	72%	$59,824
63	548	541	39%	23%	65%	$69,347
64	466	466	48%	34%	29%	$49,829
65	440	433	23%	93%	78%	$45,081
66	499	492	20%	12%	76%	$50,453
67	519	501	27%	53%	59%	$60,960
68	552	558	52%	35%	65%	$57,902
69	534	521	37%	19%	65%	$88,100
70	613	598	65%	29%	61%	$86,381
71	405	408	39%	97%	68%	$42,661
72	399	397	31%	87%	47%	$32,708
73	528	514	29%	42%	62%	$90,849
74	433	435	29%	84%	79%	$44,065
75	459	457	28%	85%	72%	$50,421
76	514	509	27%	38%	64%	$61,332
77	502	492	26%	18%	75%	$62,372
78	594	578	56%	26%	39%	$134,400
79	550	551	57%	32%	74%	$40,909
80	534	527	39%	39%	65%	$49,877
81	491	483	27%	57%	72%	$63,030
82	496	491	29%	21%	75%	$53,465
83	500	490	19%	26%	71%	$49,335
Total	**512**	**502**	**32%**	**43%**	**65%**	**$70,231**

Table 10: Filter by high school segments

2011 D+ Cluster	SAT Math	SAT CR	Going Out of State	Percent NonWhite	Need Financial Aid	Med Income
51	462	457	14%	33%	68%	$40,918
52	489	496	81%	99%	77%	$64,730
53	471	484	28%	38%	62%	$60,833
54	376	371	33%	96%	38%	$38,146
55	489	481	39%	46%	44%	$71,845
56	536	508	73%	43%	49%	$63,967
57	434	435	29%	82%	79%	$48,301
58	592	577	51%	27%	32%	$104,509
59	499	489	19%	18%	74%	$47,685
60	523	549	23%	30%	33%	$70,175
61	485	370	33%	89%	9%	$61,385
62	474	473	34%	92%	67%	$55,515
63	440	427	28%	86%	72%	$49,238
64	606	542	37%	89%	57%	$81,911
65	515	503	28%	43%	65%	$72,692
66	498	515	37%	37%	73%	$60,272
67	526	546	48%	41%	69%	$71,279
68	541	540	41%	26%	62%	$79,260
69	390	395	36%	92%	74%	$43,391
70	595	581	56%	33%	48%	$105,721
71	400	412	57%	98%	80%	$43,137
72	528	544	35%	25%	64%	$70,018
73	451	438	24%	89%	76%	$48,406
74	654	579	76%	80%	46%	$59,089
75	514	502	31%	20%	71%	$72,850
76	600	584	72%	50%	28%	$90,265
77	595	508	64%	75%	39%	$39,490
78	473	468	48%	43%	22%	$56,703
79	594	585	61%	26%	71%	$65,180
Total	**514**	**502**	**32%**	**44%**	**65%**	**$70,223**