A Sociological Analysis of Structural Racism in Student List Products

ABSTRACT

Universities 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 Latinx students. We motivate critical policy research on third-party products and vendors in education.

1 Introduction

Colleges and universities (herein universities) identify prospective students by purchasing "student lists" from College Board, ACT, and other vendors. A student list contains the contact information of prospective students who meet the search filter criteria (e.g., test score range, high school GPA, zip codes) specified by the university. Purchased lists are a fundamental input for undergraduate recruiting campaigns (EAB, 2018), which target individual prospects by mail, email, and on social media.

Research suggests that student lists are important for college access and degree completion for millions of students each year. Howell et al. (2021) compared SAT test-takers who opted into the College Board Student Search Service – allowing accredited institutions to "licence" their contact information – to those who opted out.[1] Figure 1 reproduces the main results. After controlling for covariates (e.g., SAT score, parental education), 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%).

However, a series of *TICAS* reports argue that student list products systematically exclude underrepresented students in two ways (Author, XXXXa, XXXXb, XXXXc). First, student list products sold by College Board and ACT have historically excluded non test-takers, but rates of test-taking differ by race and class (Blake & Langenkamp, 2022; Hyman, 2017). Second, several search filters (e.g., AP score, geodemographic segment) used to control which prospect profiles are purchased facilitate the exclusion of students from communities of color and low-income communities.

Prior scholarship on recruiting assumes that recruiting is something done by individual universities (e.g., Author, XXXXd; Stevens, 2007), but university recruiting behavior is

[1] For a similar analysis of ACT's Educational Opportunity Service see Moore (2017).

structured by third-party products from vendors and consultancies in the enrollment management industry (Author, XXXXa). The nascent "platform studies in education" literature observes that third-party platforms increasingly perform core functions in education and calls for critical scholarship to inform policy regulations about edtech (Nichols & Garcia, 2022). However, the literature has not investigated how third-party platforms structure educational opportunity along the dimensions of race, class, and geography. This study investigates the College Board Student Search Service product. We ask, what is the relationship between student list search filters and the racial composition of students who are included versus excluded in student lists purchased from College Board?

We develop a conceptual framework by drawing from scholarship about algorithmic products from the sociology of race and critical data studies. Student list products are algorithmic selection devices that — similar to Google Ads or Facebook – allow advertisers to control the prospective customers through the use of search filters. Structural racism is systematic racial bias in which processes viewed as neutral or common-sense systematically advantage dominant groups (Bonilla-Silva, 1997; Ray, 2019). Scholarship from critical data studies shows how platforms reinforce racial inequality by embedding structural inequality within platform algorithms (e.g., Benjamin, 2019; Noble, 2018). Structurally racist inputs are determinants of a selection device that are correlated with race because non-white people have been historically excluded from the input (Hirschman & Bosk, 2020). We conceptualize several student list search filters (e.g., zip code, AP exam score) as structurally racist inputs that reflect historical inequality in educational opportunity. We develop propositions about the relationship between structurally racist search filters and racial exclusion.

We assess propositions using a nationally representative sample of high school students from the High School Longitudinal Study (HSLS:09) and also data about student lists purchased by public universities, which we collected via public records requests. We reconstruct search filters and filter thresholds from the College Board Student Search Service product. We simulate student list purchases using theoretically motivated and commonly observed search filters with the goal of understanding how combinations of search filters and filter thresholds yield racial inequality in included versus excluded prospects.

The manuscript is organized as follows. First, we provide background on student list products, situating them vis-a-vis the process of recruiting students and summarizing recent dynamics in the market for student list data. Second, we review empirical scholarship on recruiting, focusing on scholarship from sociology. Third, we develop a a conceptual framework and propositions. Next, we describe methods and present results. Finally, we discuss implications for policy and scholarship. We argue that particular College Board search filters may satisfy the "unfair practices" criteria of the FTC Act. Our broader contribution is to scholarship on education policy. In concert with scholarship on digital platforms in education (e.g., Nichols & Garcia, 2022), we propose a critical policy literature that examines third-party products and vendors in education with the goal of informing regulatory action. As conservative courts challenge progressive policies like affirmative action, policy research should go on the offensive, using theories of structural inequality to investigate structural racism by edtech.

2 Background: Student List Products

2.1 Situating Lists Vis-a-vis Recruiting

Student lists are a match-making intermediary connecting universities to prospective students. The U.S. higher education market can be conceived as a national voucher system, whereby tuition revenue – including household savings and financial aid – follow students to whichever institution they enroll in. Students want to attend college but do not know all their options, where they would be admitted, and how much it will cost. Universities pursue some mix of broad enrollment goals (e.g., tuition revenue, academic profile, racial diversity), while also meeting the needs of various campus constituencies (e.g., College of Engineering needs majors). Universities cannot realize these goals solely from prospects who contact the university on their own. They must find prospects who can be convinced to apply. However, universities don't know who they are, where they are, or how to reach them. Student lists overcome the problem faced by universities, providing the contact information of prospects who satisfy their criteria of enrollment goals.

Figure 2 depicts the "enrollment funnel," a conceptual model used in the enrollment management industry to describe stages in the process of recruiting students. The funnel begins with a large pool of "prospects" (i.e., prospective students) that the university would like to convert into enrolled students. "Leads" are prospects whose contact information (or "profiles") has been purchased. "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 enrollment funnel informs interventions that increase the probability of "conversion" from one stage to another (Campbell, 2017). For example, financial aid packages are used to convert admits to enrolled students.

At the top of the enrollment funnel, universities identify leads by buying student lists. The sum of purchased leads plus student-as-first-contact inquiries constitutes the set of all prospects the university has contact information for who may receive targeted recruiting interventions. Based on a survey of their clients, Ruffalo Noel Levitz (2020) reported that 28% of public universities purchased less than 50,000 names annually, 44% purchased 50,000-100,000 names, 13% purchased 100,000-150,000 names, and 15% purchased more than 150,000 names. 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 university, 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%).[2]

2.2 The Market for Student List Data

In the 21st Century, student lists have had a surprising level of dynamism in the broader enrollment management industry. Author (XXXXa) describes key dynamics that shaped the contemporary market for student list data. First, enrollment management consulting firms are central to the student list business. Many universities outsource student list purchases to

[2]For private non-profit institutions, 34% of private institutions purchased fewer than 50,000 names, 24% purchased 50,000-100,000 names, 23% purchased 100,000-150,000 names, and 18% purchased more than 150,000 names (Ruffalo Noel Levitz, 2020). Additionally, 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).

enrollment management consulting firms. Furthermore, student lists are an essential input to the predictive models and recruiting interventions (e.g., emailing prospects) the consultancies provide.

The second dynamic is competition in the 2000s followed by concentration in the 2010s. Scholarship on platform capitalism defines data rent as "digital traces" created by users ineracting with a platform (Sadowski, 2019). Student list data are data rent extracted from the user-data of students laboring on platforms (e.g., taking the SAT). Historically, the student list business has been dominated by College Board and ACT. In the 2000s, advances in technology yielded new sources of student list data, creating opportunities for new vendors. Start-ups entered the student list market by creating college search engines that asked students to submit information in order to receive recommendations about colleges and scholarships. Another new data source is college planning software (e.g., Naviance) sold to high schools and used by high school students and guidance counselors.

In the 2010s, the enrollment management industry experienced a surge in horizontal followed by vertical acquisitions. Horizontal acquisitions occurred when an enrollment management consulting firm acquired a competitor (e.g., e.g., RuffaloCODY acquired Noel-Levitz in 2014). Vertical transformations also transformed the student list business. For example, K-12 software provider PowerSchool entered the student list business by acquiring the Naviance college planning and Intersect student recruiting platforms from Hobsons. One of the largest enrollment consultant, EAB, entered the market for student list data through acquisitions (e.g., Cappex college search engine) and by becoming the exclusive reseller of the Intersect.

Third, incumbents College Board and ACT attempted to retain their competitive advantage amidst the test-optional movement. Both organizations embraced data science by developing new search filters (e.g., ACT's "Enrollment Predictor") based on statistical models. Additionally, both organizations leveraged their oligopoly position in the student list business to sell enrollment management consulting, offering clients information about prospects that is not included in purchased lists. However, the test-optional movement poses an existential threat. As fewer prospective students take College Board and ACT assessments, their competitive advantage in the coverage of college-going high school students is eroding, and private equity edtech firms such as EAB and PowerSchool are positioned to acquire market share. Whereas College Board and ACT historically sold names at a price per-prospect (e.g., $0.50 in 2021), for-profit edtech firms maximize profit by wrapping a large proprietary database of prospects within a software-as-service product (e.g., EAB's Enroll360) that universities must purchase in order to obtain access to these prospects.

3 Scholarship on Recruiting from Sociology

Most scholarship on enrollment management focuses on latter stages of the enrollment funnel, particularly which applicants get admitted and financial aid leveraging to convert admits to enrolled students. Fewer studies investigate the earlier "recruiting" stages of identifying prospects, acquiring leads, and soliciting inquiries and applications. We review scholarship on recruiting from sociology, identifying a blind spot shared by scholarship from other disciplines. Scholarship from sociology primarily utilizes ethnographic or case-study designs, and often analyzes recruiting as part of a broader analysis of college access or enrollment management. This literature has analyzed recruiting from the perspective of students, high schools, and postsecondary institutions (Author, XXXXd; e.g., Holland, 2019; McDonough, 1997; Posecznick, 2017; Stevens, 2007). For example, Holland's (2019) analysis of pathways from high school to college exemplifies scholarship that engages with recruiting from the perspective of high school students.

Several studies analyze connections between colleges and high schools from an organizational perspective. Off-campus recruiting visits are often conceptualized as an indicator of enrollment priorities and/or a network tie indicating the existence of a substantive relationship (Author, XXXXe). Stevens (2007) provides an ethnography of enrollment management at a selective liberal arts college. The college valued recruiting visits to (affluent) high schools as a means of maintaining relationships with guidance counselors at feeder schools. Khan (2011) analyzes the other side of the coin, showing how guidance counselors at an elite private school get under-qualified applicants into top colleges by exploiting colleges' desire for information about which applicants will enroll if admitted. Author (XXXXd) 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. Author (XXXXf) analyzed off-campus recruiting visits by public research universities to out-of-state metropolitan areas, finding that universities engage in "recruitment redlining – the circuitous avoidance of predominantly Black and Latinx communities along recruiting visit paths" (p. X).

A smaller set of studies analyze recruiting at open-access institutions that target working adults (e.g., Cottom, 2017; Posecznick, 2017). Cottom (2017) is simultaneously an ethnography of enrollment management by for-profits and an analysis of the political economy. For-profits found a niche in Black and Latinx communities precisely because traditional universities ignored these communities. They systematically targeted women of color, particularly Black women and generated profit by encouraging these students to take on federal and private loans. This business model exemplifies "predatory inclusion," the logic of "including marginalized consumer-citizens into ostensibly democratizing mobility schemes on extractive terms" (Cottom, 2020, p. 443).

Collectively, empirical scholarship on recruiting assumes that recruiting is something done by individual colleges and universities. As a consequence, the recruiting literature ignores the role of third-party products and vendors. This blind spot has two root causes. First, scholarship on recruiting has not considered scholarship from critical data studies, which shows that digital platforms perform core organizational functions (e.g., Sadowski, 2019, 2020) based on algorithms that reinforce racial inequality (e.g., Benjamin, 2019). Second, scholarship on recruiting ignores the enrollment management industry that surrounds universities.

Author (XXXXa) provide a conceptual analysis of the market for student list data in relation to the enrollment management industry. Although universities make choices about which names to purchase, these choices are structured by the algorithmic architecture of student list products — which prospects are included in the product, the targeting behaviors allowed and encouraged by the product. Furthermore, many universities are uninformed about which prospective students they target because they outsource student list purchases to enrollment management consultancies. Nevertheless, these student list purchases substantially determine which prospective students will receive recruiting interventions at subsequent stages of the enrollment funnel. Thus, products and services sold by third-party vendors structure the recruiting behavior of individual universities and, in turn, college access opportunities for students.

Author (XXXXb) issued public records request to collect data about student lists purchased by public universities in four states. Their analyses sought to investigate the College Board student list product, rather than the behavior of universities purchasing the product. The primary research question was, what is the relationship between student list filter criteria and the characteristics of prospects included in purchased lists? For example, an analysis of several "women in STEM" purchases – which filtered on a combination of SAT/AP score, GPA, state, and intended major – showed that the racial and socioeconomic composition of targeted prospects differed dramatically from their surrounding metro area. However, because of data limitations – a non-random sample of student list purchases, Author (XXXXb) could not determine which filters were driving this exclusion.

This paper advances beyond Author (XXXXb) in two ways. First, we develop theoretically motivated propositions about which search filters are likely to yield racial inequality. Second, we test propositions using a nationally representative sample of high school students. These data allow us to examine who is included as filters and filter thresholds are changed. The analyses yield inferences that generalize to student populations of interest to policymakers.

4 Conceptual Framework

We introduce concepts at the nexus of algorithms and structural racism, drawing from the sociology of race and also from critical data studies and critical geography. Next, we apply these concepts to develop propositions about the relationship between student list search filters and racial exclusion.

4.1 Algorithms and Structural Racism

Algorithms and actuarialism. Algorithms are "sets of instructions written as code and run on computers" (Burrell & Fourcade, 2021, p. 215). Sociologists observe that algorithmic products utilize actuarial methods and are based on the logic of actuarialism (Burrell & Fourcade, 2021; Hirschman & Bosk, 2020; Simon, 1988). Actuarial methods – pioneered by the insurance industry – proceed in two steps. First, apply statistical techniques to previous cases in order to identify factors positively and negatively associated with an outcome of interest. Second, apply these results to future cases in order to make predictions and to assign levels of risk to each case. Actuarialism is the ideology that equates fairness with risk, as determined by predicted probabilities. Under the logic of actuarialism, entities that have characteristics associated with loan default should be charged higher interest rates.

Actuarial methods standardize decision-making by replacing individual judgment with decisions based on a formula. Selection devices are "standardization tools designed for making categorical decisions about individuals" (Hirschman & Bosk, 2020, p. 349) "solely on the basis of their assigned scores" (Duncan, Ohlin, Reiss, & Stanton, 1953, p. 572) on one or more selection instruments, such as a test. Examples of selection devices include student list products or an algorithm that uses GPA and SAT score to determine which applicants are accepted.

Hirschman & Bosk (2020) states that actuarial methods can promote racial inequity *if* the primary source of inequality is racial bias of individual decision-makers. For example, Korver-Glenn (2018) shows that homes in white neighborhoods received higher appraisal values than those in non-white neighborhoods because appraisers have discretion in selecting comparision homes ("comps") for the valuation. The adoption of actuarial methods across many industries was buoyed by concerns about racial equity following anti-discrimination legislation in the 1970s (Burrell & Fourcade, 2021).

However, the sociology of race argues that actuarial methods do not reduce racial inequality stemming from structural racism. Drawing from Bonilla Silva's (1997) concept of "racialized social systems," structural racism is defined as "a form of systematic racial bias embedded in the 'normal' functions of laws and social relations" (Tiako, South, & Ray, 2021, p. 1143), whereby processes viewed as neutral or common-sense systematically advantage dominant groups and disadvantage marginalized groups. Hirschman & Bosk (2020) states that "actuarialism tends to bake [racial] inequality into the decision-making process, transmuting social disadvantages into seemingly objective measures of individual riskiness" (pp.352-353).

We discuss two mechanisms of structural racism in algorithmic products: (1) structurally racist inputs; and (2) market segmentation and micro-targeting.

Structurally racist inputs. Actuarial products predict future outcomes by modeling the determinants of the outcome using historical data. Burrell & Fourcade (2021) state that "predicting the future on the basis of the past threatens to reify and reproduce existing inequalities of treatment by institutions" (p. 224). Even when actuarial products do not include race as a determinant, they often include determinants that are highly correlated with race. *Structurally racist inputs* are determinants of an outcome that systematically disadvantage historically dominated racial/ethnic groups because these groups have been historically excluded from this input (Harcourt, 2015; Hirschman & Bosk, 2020).

Obermeyer et al. (2019) provide an empirical example of structurally racist inputs. An algorithm that hospital systems used to predict patient health care needs under-predicted the needs of Black patients because the algorithm used healthcare costs as a proxy for needs, but Black patients tend to receive less care than others relative to their needs. In another example, Norris (2021) reconstructed Moody's city government credit rating algorithm, which assigns credits scores to cities based on determinants thought to predict loan default. The algorithm does not include the percent of residents who are Black, but does include median household income, which is correlated with percent black because of historic wage discrimination. Once the model includes household income, percent Black is no longer a significant predictor of city credit rating. Thus, household income is a "racialized input," defined as a seemingly neutral, structurally racist input that masks the structural racism of an algorithm by "explaining away" the relationship between race and the outcome.

Algorithmic selection devices often use geography as an input (Benjamin, 2019). Targeting by race can be profitable but is often illegal. Structurally racist geographic inputs capitalize on residential segregation to circumvent laws prohibiting race as an input. Thus, "racialized zip codes are the output of Jim Crow policies and the input of New Jim Code practices" (Benjamin, 2019, p. 147).

The concepts "space" and "place" from critical geography provide insight about structurally racist geographic inputs (Agnew, 2011; Bell, 2007). Place denotes a holistic understanding of a geographic location that incorporates the "history, peoples, and purposes within the political, social, and economic landscape" (Bell, 2007, p. 317). By contrast, space simply refers to a physical location which can be described in terms of quantifiable spatial features (e.g., distance, demographics, economic activity). Geospatial analyses typically adopt this view of space "as a location on a surface where things 'just happen' " (Agnew, 2011, p. 318).

Market research conceives of geography as space and exploits racial segregation as a means of identifying customers (Benjamin, 2019; Noble, 2018). For example, geodemography is a branch of market research that estimates the behavior of consumers based on where they live. College Board (2011) develops geodemographic segment search filters, stating that "the basic tenet of geodemography is that people with similar cultural backgrounds, means, and perspectives naturally gravitate toward one another or form relatively homogeneous communities; in other words, birds of a feather flock together" (p. 1). By contrast, structural analyses of racial segregation conceive of geography as place (e.g., Harris, 1993; Korver-Glenn, 2018; Rothstein, 2017). These analyses view segregation as a consequence of historic and contemporary laws, policies, and practices promoting residential segregation. Algorithmic selection devices that categorize people based on geographic location (space) without considering structures that produce segregation (place) are likely to reproduce historical race-based inequality in opportunity.

Market segments and micro-targeting. Another source of structural racism in algorithmic products are the related processes of market segmentation and micro-targeting. Market segmentation categorizes customers into groups (e.g., "married sophisticates," "rural everlasting") that are useful for advertisers (Federal Trade Commission, 2014). Micro-targeting is the process of using data to precisely identify granular segments of society (Cotter, 2022).

Sociology conceives of market segmentation as an example of "classification situations." Related to the selection devices concept, Fourcade & Healy (2013) define classification situations as the use of actuarial techniques to categorize consumers into different groups. Historically, classifications were binary; consumers with "good" credit were offered loans and those with bad credit were not. Advances in data analytics (e.g., individual credit scores) enabled finer classifications, classifying customers into many groups, or along a continuum. These classifications are tied to tiered products that targets different consumer groups with different levels of benefits and costs. For example, "payday loans" charge high interest rates to consumer groups that were previously denied credit altogether. Thus, at one end of the continuum, contemporary classification situations produce "predatory inclusion" (Cottom, 2017, 2020). At the other end of the continuum, marginalized populations are excluded from attractive product offerings.

Scholarship from critical data studies shows that racial exclusion is a predictable consequence of market segmentation (Cotter, Medeiros, Pak, & Thorson, 2021; Noble, 2018). The process of developing a classification system requires developers to make a series of inherently subjective decisions (e.g., who is in the dataset, which measures to utilize, which categories to identify), creating opportunities for individual biases of developers and structurally racist inputs to enter the algorithm (Noble, 2018). Because classification systems are developed to optimize profit, Cotter et al. (2021) argue, "audiences are treated as a commodity to be bought and sold. When audience segments are under-valued in the market, demand among advertisers for the ability to reach them will be relatively low, which decreases the likelihood that a corresponding segment will be produced" (p.3).

Scholarship on micro-targeting from critical data studies raises similar concerns. In their analysis of Facebook, Cotter et al. (2021) state that micro-targeting is "driven not by a goal of making all users available to advertisers, but of making the 'right' individuals available. [Therefore] Facebook advises that advertisers 'Implement a targeting strategy that focuses on reach and precision and eliminates waste' " (p. 1). A theme from scholarship on micro-targeting in politics is that these technologies *could* be used to to increase outreach to marginalized groups, but in practice they are not (Cotter, 2022). Instead, according to Kreiss (2012), "campaigns routinely 'redline' the electorate, ignoring individuals they model as unlikely to vote, such as unegistered, uneducated, and poor voters" (p. 74-75).

4.2 Mechanisms of Exclusion in Student List Products

Conceptualizing student-list products. Student list products are algorithmic selection devices that enable universities to select prospective students from within some database of prospects by choosing search filters.

Student list products have similarities and differences to algorithmic products that have been analyzed within sociology and critical data studies. Sociologists often study algorithmic products that assign scores based on the value of input determinants. For example, Moody's algorithm assigns credit scores to cities based on inputs correlated with default in previous cases (Norris, 2021). Similar to these analyses, student lists utilize search filters that can be conceptualized as structurally racist inputs. For example, College Board Student Search Service enables universities to filter prospects based on 5-digit zip code, but zip codes are racially segregated.

Algorithmic products that make decisions purely based on scores (e.g., most credit offers) remove racial inequality caused by explicit or implicit individual decision-making bias (Hirschman & Bosk, 2020). By contrast, student list products are similar to purchasing ads from Google or Facebook in that advertisers (universities) choose prospective customers by selecting on search filters. Universities purchasing lists may be thoughtful about avoiding structurally racist search filters. However, this individual discretion raises the possibility of racial disparities due to individual bias or lack of knowledge about the products.

Market segmentation and micro-targeting are central to student list products. Consulting firms encourage universities to execute multiple student list purchases, each targeting different market segments (e.g., Waxman, 2019). Purchases target granular populations by simultaneously filtering on several filters. As in political advertising (Cotter, 2022), micro-targeting 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.) while ACT Encoura uses the tag-line "find and engage your best-fit students" Encoura (n.d.). Student list products have developed new search filters based on predictive analytics. For example, College Board (2011) utilized market segmentation methodologies to create "geodemographic segment" filters, which classify each high school and each neighborhood to a group based on the past college-going behaviors of students. College Board added three new geodemographic filters in 2021 (College Board, 2021). Other new filters are designed to increase precision, for example ACT's predicted probability of enrollment filter. To the extent that universities want to target students from affluent schools and communities (Author, XXXXd), contemporary student list products facilitate this goal with great efficiency.

4.2.1 Predicting Exclusion

Our analyses focus on exclusion due to structural inequality embedded in the underlying student list product, as opposed to exclusion that emerges from the individual bias of people purchasing lists. We posit two broad sources of structural inequality in student list products: (1) who is included in the underlying database; and (2) utilizing structurally racist inputs as search filters for selecting prospects from the underlying database. Search filters in the College Board Student Search Service can be categorized into the four buckets of academic, geographic, demographic, and student preferences (e.g., desired campus size, intended major). Drawing from theory, we develop propositions about the relationship between search filters and exclusion, focusing on academic and geographic search filters.

Academic filters. College Board academic filters include high school graduating class, SAT score, PSAT score, AP score by subject, high school GPA, and high school class rank.

The first source of structural inequality in student list products is which prospective students are included in the underlying database. 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). 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.

Prior research shows that rates of SAT/ACT test-taking differ by race and class (e.g., Bastedo & Jaquette, 2011; Blake & Langenkamp, 2022; Hyman, 2017). Similarly, the percentage of students who take AP exams vary across race, particularly for STEM exams (Kolluri, 2018), and 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, which we analyze separately by assessment (SAT, PSAT, AP) and for taking any assessment.

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

Second, search filters that condition on test scores thresholds are a source of exclusion that builds on differences in test-taking. Average standardized test scores differ by race and by class (Alon, 2009; Alon & Tienda, 2007). Research finds that access to test preparation varies by race and class (Park & Becks, 2015). Furthermore, prior research finds that SAT question items are racially and socioeconomically biased (Freedle, 2003; e.g., Santelices & Wilson, 2010). Therefore, we conceptualize test score filters as a structurally racist input. By contrast, prior research suggests that high school GPA is a less biased measure of performance (Alon & Tienda, 2007; Posselt, Jaquette, Bielby, & Bastedo, 2012) and that GPA is a strong predictor of postsecondary student success (Allensworth & Clark, 2020; Niu & Tienda, 2010). We test the following proposition separately by assessment (SAT, PSAT, AP) and for GPA:

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 universities to target prospects based on where they live. College Board geographic search filters include state, CBSA, county, and zip code. Additionally, the geomarket filter and geodemographic filters create new borders based on historical College Board data, but we do not currently have access to these borders.

We conceptualize geographic search filters as structurally racist 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 (space) without consideration to the structures that produce racial segregation (place) is likely to reinforce historical race-based inequality in educational opportunity.

Prior research on recruiting consistently finds that selective private and public research universities disproportionately target affluent schools and communities (Author, XXXXf, XXXXd, XXXXe; Stevens, 2007). These findings suggest that universities may filter on affluent zip codes when purchasing student lists. 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 in student lists declines relative to the proportion who are excluded.

University recruiting behavior often targets prospects in particular metropolitan areas (Author, XXXXb, XXXXd). When targeting metropolitan areas, we expect that utilizing finer geographic filters (e.g., zip code rather than county) is associated with greater racial dispairities in student list purchases because American residential segregation occurs at fine-grained geographic levels (Korver-Glenn, 2022).

P4. Filtering on smaller geographic localities is associated with greater racial disparities in included vs. excluded than filtering on larger geographic localities.

Filtering on multiple filters. Actual student list purchases filter on several criteria rather than one. Author (XXXXb) analyzed data on 830 student lists purchased by 14 public universities. The average purchase specified 4.44 criteria and 98.8% of purchases simultaneously specified at least one academic and one geographic filter. Table 1 shows the top 20 filter combinations. Filtering on multiple search criteria facilitates micro-targeting of desired prospects. The flipside of micro-targeting is exclusion. We suggest that filtering on multiple structurally racist inputs has a compounding effect on racial inequality in which prospects are included versus excluded. To assess this claim, we draw on the Author (XXXXb) sample of orders placed by public universities and select several orders that utilized common, but potentially problematic filter criteria. We analyze the racial composition of students included versus excluded from these purchases. Next, we simulate marginal changes to order criteria to gain insight about how structurally racist inputs drive exclusion.

5 Methods

5.1 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.

Our 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.[3] 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.

The second data source consists of "order summaries" for student lists that public universities purchased from College Board. These data are used to inform hypothetical student list purchases in the final set of analyses. As described in Author (XXXXb), we collected these data 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. Author (XXXXb) analyzed 830 College Board orders, which yielded more than 3.6 million prospect profiles. These orders were placed by 14 public universities. Figure 3 shows the filters utilized in these orders.

5.2 Variables

Our research question is, what is the relationship between student list search filters and the racial composition of students who are included versus excluded from College Board student list purchases? In turn, our dependent variable measures student demographic characteristics and our independent variables are measures of student list filters. Descriptive statistics for analysis variables are shown in Table 2.

Dependent variable. Our primary dependent variable is 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

[3] Unwighted sample was rounded to 10 to meet restricted data regulations by NCES

White, non-Hispanic.[4]

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 3. 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 high school GPA in academic courses (X3TGPAACAD), which is a question asked in the pre-test questionnaire of College Board assessments. 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.

Propositions **P3** and **P4** focus on geographic filters. Drawing from Figure 3, we create measures for student county (X2GCNTY), zip code (X2GZIPCD), and CBSA (based on crosswalk with home zip code). Next, we attach income data to localities by merging in data from the American Community Survey (ACS) 2012 5-year estimates. We do not create independent variables for geomarket filter or geodemograhic segment filter because these filters utilize geographic borders based on proprietary College Board data.

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

5.3 Analyses

Analyses utilize simple descriptive statistics, with appropriate statistical tests. All analyses compare the racial composition of included versus excluded prospects when particular filters and/or filter thresholds are utilized to purchase prospect profiles.

Consider a hypothetical purchase that all prospects 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 5.05% (`=91/1803`) of AP STEM test-takers and Black students comprise 10.6% (`=1564/14722`) 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. This comparison focuses on the racial composition of prospects targeted from the university perspective; that is, what is the racial composition of prospects who are targeted by a particular set of filters versus the racial composition of prospects who are excluded by these filters?

Analyses for propositions P1 through P4 examine purchases that utilize individual filters in isolation. The final set of analyses examine purchases that utilize academic and geographic filters in combination with one another, with choice of filters informed by commonly observed combinations from the public request data and also by theoretical considerations.

5.4 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.

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 HSL09 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). Our analysis of structurally racist inputs and exclusion yields insights across student list products. 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.

6 Findings

6.1 Academic Filters

We begin by describing the racial characteristics of prospects who completed standardized assessments in comparison to those who did not, which determines inclusion in the underlying College Board student list database. Figure 4 presents the racial/ethnic composition of prospects included (i.e., completed assessment) and excluded (i.e., did not complete assessment) across SAT, PSAT, and AP exams. For example, the top left graph shows that more than 1.8 million prospects completed the SAT and would have presumably been included in the College Board student list database. In comparison, more than 2.3 million prospects did not complete the SAT and would be excluded from the database. White students make up 53% of included students who completed the SAT and 51% of excluded students who did not. 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 ($p<0.000$). 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 ($p<0.000$). Black students similarly make up 12% of included prospects but 15% of excluded prospects ($p<0.000$).

Other standardized assessments resulted in similar included prospects that were 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 4 also shows the composition of included versus excluded prospects by AP exam completion in any subject on the top right panel. Similar to SAT, White (54% versus 51% White) and Asian students (8% versus 3%) make up statistically significant ($p<0.000$) larger proportions of included prospects. While an equal proportion of included and excluded students are Hispanic (22%), Black students make up a smaller share ($p<0.000$) 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 suggests 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 students at minimum score thresholds commonly used across student list purchase orders for SAT, PSAT, and AP exams. For example, Figure 5 presents these results for SAT (left panel) and PSAT assessments (right panel). For the top left panel, each bar represents the racial composition of included prospects who completed the SAT exam and scored at the minimum threshold indicated. On the bottom left panel of Figure 5, each bar represents the racial composition of excluded prospects who did not complete the SAT 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 5 are reported in online appendices for space considerations.

As SAT score thresholds increase from less than 1000 to greater than 1400 in Figure 5, 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 ($p<0.000$) smaller share of included (47%) than excluded (53%) prospects scoring less than 1000 on the SAT, 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).

While making up relatively small proportions of the overall sample, declines in proportions of American Indian/Alaska Native students and Native Hawaiian/Pacific Islander students within included versus excluded prospect groups are statistically significant as score thresholds increase (online Appendix A). In order to more equitably capture these differences, we report the number of students rather than their overall representational proportion within included versus excluded groups. For instance, more than 7,600 American Indian/Alaska Native students and nearly 2,500 Native Hawaiian/Pacific Islander students are represented in the included prospects relative to the more than 20,800 and 16,300 represented in the excluded prospects at SAT scores less than 1000, respectively. However, American Indian/Alaska Native students decline to zero and Hawaiian/Pacific Islander students decline to 435 students in the included prospects group by the 1300 or greater SAT score threshold.

PSAT results are also shown in Figure 5 for composite scores that range from 60 to 240. [5]

[5] PSAT exams taken 2014 or before receive composite scores that range from from 60 to 240. PSAT

Similar to SAT, as PSAT 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. Online appendices show all comparisons between included and excluded students across PSAT score thresholds are statistically significant at the $p<0.000$ level, with the exception of multiracial students at the 220 or greater minimum score threshold.

We find similar racial disparities in included versus excluded prospects across AP exam score thresholds, providing strong support for Proposition P2. Figure 6 shows similar results as Figure 5 for AP exams. As AP score thresholds for any subject exam (left panel) increase from one to five, proportions of included White and Asian students increase while proportions of included Hispanic, Black, Multiracial, American Indian/Alaska Native, and Native Hawaiian/Pacific Islander decrease relative to excluded prospects. For example, the 110,360 included prospects (relative to excluded prospects) who had a score of one on any subject AP exam were on average 38% White (52% excluded), 6% Asian (4% excluded), 27% Hispanic (22% excluded), and 21% Black (14% excluded). By an AP score threshold of four or greater, included prospect proportions shift (relative to excluded) to 60% White (51% excluded), 10% Asian (3% excluded), 20% Hispanic (22% excluded), and 4% Black (4% excluded).[6] Similar patterns are evident for AP STEM exam completion (right panel).

Given differences in completion rates for standardized assessments by race, our conceptual framework outlines an interest in whether using GPA filters leads to greater racial parity between included versus excluded students relative to standardized assessments as thresholds increase. We therefore analyze the racial composition of included versus excluded students at minimum thresholds commonly used across student list purchase orders for high school GPA. Figure 7 shows the racial composition of included (top panel) and excluded (bottom panel) students across less than 2.0, 2.0 or greater, 3.0 or greater, and 3.5 or greater thresholds of GPA. Similar to standardized assessments, Figure 7 suggests proportions of included prospects

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. CITE

[6] Proportional differences for these specific racial/ethnic categories at reported score thresholds are statistically significant at the $p<0.000$ level and reported in online appendices

increase for White students and Asian students (although modestly) while proportions of included prospects decrease for Hispanic and Black students as GPA thresholds increase. For instance, White student proportions increase from 37% (relative to 57% excluded, p<0.000) at GPA less than 2.0 to 71% (relative to 57% excluded, p<0.000) at GPA 3.5 or greater. On the other hand, Hispanic and Black included student proportions (relative to excluded proportions) decrease from 30% (19% excluded, p<0.000) and 22% (11% excluded, p<0.000) at GPA less than 2.0 to 11% (24% excluded, p<0.000) and 4% (15% excluded, p<0.000) at GPA 4.0 or greater, respectively. The 12,591 American Indian/Alaska Native students included at GPA less than 2.0 (15,928 excluded, p<0.000) also decline to 1,304 (27,216 excluded, p<0.000) at GPA 3.5 or greater score threshold.

However, Figure 7 shows that GPA filters at "middle" thresholds (2.0 to 3.0) lead to smaller declines in proportions of included Hispanic and Black students relative to middle thresholds of SAT and PSAT filters. In increasing GPA from 2.0 or greater to 3.0 or greater, the proportions of Hispanic and Black included students decrease by 3 percentage points or less. In comparison, increasing PSAT from scores 120 or greater to 200 or greater results in an up to nine percentage point decrease in the number of included Black students. This pattern of lesser relative declines in the proportion of underrepresented minority students included at "middle" thresholds is also evident by AP filters (see Figure 6). However, given the disparities in AP course availability and exam completion rates, a considerable smaller number of overall included students are captured by AP filters than GPA.

6.2 Geographic Filters

Proposition P3 and Proposition P4 conceptualize how the use of geographic filters may result in greater racial disparities in proportions of included prospects relative to excluded prospects. For instance, Proposition P3 suggests as purchases filter on higher levels of zip code affluence, the proportion of underrepresented minority students included in student lists will decline relative to the proportion who are excluded. In order 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 Core Based Statistical Areas (CBSA). For example, median household income percentiles based on the 378 zip codes within the Los Angeles metropolitan area are \$55,256 at the 20th percentile, \$70,804 at the 40th percentile, \$89,709 at the 60th percentile, and \$108,316 at the 80th percentile (in 2022 CPI). So the Los Angeles zip code 92649, which captures parts of the Huntington Beach area, with a median household income of \$109,159 (in 2022 CPI) would be categorized as zip code in the 80th percentile of affluence within CBSA. This approach also aligns with common ways in which student list orders purchase prospect's contact information by filtering on zip codes within specific CBSAs.

Figure 8 presents the racial composition of zip codes that included (top panel) versus excluded prospects (bottom panel) when filtering based on percentile of affluence within CBSA. 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 30% and 27% of included 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 of affluence within CBSA, the proportions of Hispanic students within included prospects declines to 11% relative to making up 23% of excluded prospects ($p<0.000$). Similarly, Black students make up 9% of included prospects relative to making up 14% of excluded prospects ($p<0.000$) within the most affluent zip codes. [7]

To contextualize these findings, Figure 9 presents similar results as Figure 8 for two specific CBSAs: Los Angeles and New York. The left panel of Figure 6 shows the racial composition of included (top) and excluded (bottom) students across percentiles of zip code affluence for Los Angeles. Similar to results across all CBSAs in Figure 8, proportions of included prospects relative to excluded prospects increase for White students while proportions decline for Hispanic and Black students as zip codes become more affluent. For instance, White student proportions increase from 5% (relative to 17% excluded, $p<0.000$) at the 20th percentile, to 28% (relative to 12% excluded, $p<0.000$) at 50th-79th percentiles, and up to making up

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

76% of included prospects (relative to 12% excluded, p<0.000) for zip codes at the 90th percentile or higher of affluence. On the other hand, Hispanic and Black included student proportions (relative to excluded proportions) decrease from 73% (54% excluded, p<0.000) and 14% (7% excluded, p<0.000) at zip codes in the lower 20th percentiles of affluence to 4% (60% excluded, p<0.000) and 3% (9% excluded, p<0.000) at the 90th percentile or higher of affluence, respectively. While New York provides a different racial composition of students than Los Angeles, similar and statistically significant patterns persist.

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. However, we acknowledge that categorizing zip codes within CBSA limits the number of rural zip codes captured within the included prospect groups. By categorizing zip code affluence within CBSA, only rural zip codes within micropolitan statistical areas (i.e., areas that have at least one urban cluster of at least 10,000 people with commuting ties to adjacent metropolitan areas that have higher degrees of social and economic activity) will be captured via CBSA.

To analyze whether filtering on smaller geographic localities is associated with greater racial disparities in included prospects relative to excluded prospects (Proposition P4), we compare the racial characteristics of prospects based on zip code filters versus county filters. We categorize all zip codes and counties based on levels of median household income within their respective Core Based Statistical Areas (CBSA), given results for Proposition P3, to analyze whether relationships between racial composition and geographic level change across levels of affluence. Therefore, zip codes and counties are categorized as low, moderate, and high income based on their median household incomes falling below 30th percentile, within 30th-70th percentiles, or greater than 70th percentile of affluence within their respective CBSAs.

Figure 10 presents the racial composition of prospects when using zip code filters (left panel) in comparison to county filters (right panel). There are modest differences between included versus excluded groups when comparing zip code filters to county filters at low and moderate levels of affluence. For example, Hispanic students are slightly overrepresented within included relative to excluded prospects (23% versus 22%, $p<0.000$) by zip code at moderate levels of affluence but underrepresented (20% versus 22%, $p<0.000$) at moderate affluence levels for county. Similarly, Black students are slightly underrepresented within included relative to excluded prospects (12% versus 15%, $p<0.000$) by zip code at moderate levels of affluence but overrepresented (20% versus 13%, $p<0.000$) at moderate affluence levels for county.

Differences between the use of zip code filters and county filters are most evident in high levels of affluence. For instance, Hispanic and Black students make up 16% and 8% of included prospects and 24% and 16% of excluded prospects for the most affluent zip codes, respectively. However, in the most affluent counties, Hispanic students make up an equal share of included and excluded prospects (22%). Similarly, filtering on the most affluent counties leads to smaller differences in proportions of Black students within included and excluded prospects (11% versus 16%, $p<0.000$). These results suggest filtering for smaller geographic localities (i.e., zip codes) is associated with greater racial disparities in included prospects relative to excluded prospects in comparison to larger geographic localities (i.e., counties) at higher levels of affluence, which results for Proposition P3 suggest are the thresholds with the greatest lack of racial parity between included versus excluded students.

6.3 Combinations of Filters

Our last set of analyses focus on assessing whether filtering on multiple criteria compound the effect of racial disparities in which prospects are included versus excluded. We draw on Figure 3 to select common filters used across orders. We begin by combining the two most common academic filters: GPA and SAT. Figure 11 (top panel) presents the racial composition of prospects included when filtering on GPA greater than or equal to 3.0 while simulating increases to minimum SAT thresholds at increments of 50 beginning at scores just above the sample median of 1010. For space considerations, we only present included prospect groups across all combinations. The figure suggests that even at the the lowest SAT score, White students make up much larger proportions while Black and Hispanic students make up significantly smaller proportions of included prospects when filtering for both GPA and SAT. For example, White students make up 72% of included prospects when filtering for GPAs greater than or equal to 3.0 in combination with SAT scores greater than 1050, whereas

Hispanic and Black students make up 10% and 3%, respectively. Racial disparities only grow as SAT thresholds increases. Moreover, these racial disparities are greater than when filtering for similar thresholds for GPA (Figure 7) and SAT score (Figure 5) individually. The bottom panel of Figure 11 suggest similar results are evident when combining a GPA filter greater than or equal to 3.0 and a PSAT filter. While Hispanic and Black students make up larger proportions at lower thresholds of PSAT in comparison to SAT when combined with GPA, the racial disparity for Black students is still greater in the combination of filters than when filtering for similar thresholds of PSAT score (Figure 5) individually.

In order to assess the effects of combining academic and geographic filters, Figure 12 adds a zip code filter to the GPA and SAT/PSAT order simulations presented above. 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 CBSAs. The top panel of Figure 12 presents the racial composition of included students when filtering for GPAs greater than or equal to 3.0, SAT 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 with GPA and SAT filters leads much greater disparities even at lower levels of affluence. For example, Figure 12 shows White students make up 72% of included prospects when filtering for GPAs greater than or equal to 3.0 in combination with SAT 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 30% of Hispanic and 27% of Black included prospects resulting from only filtering by zip code (Figure 8). 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, although proportional differences are modest at higher incomes. Similar patterns are evident when combining similar zip code and GPA filters with a PSAT filter for composite scores greater than or equal to 150.

Lastly, we assess the racial composition of included prospects when filtering on both GPA and AP scores in Figure 13. The top panel presents the racial composition of prospects included when filtering on GPA greater than or equal to 3.0 while simulating increases in AP scores in any subject exam. Across all AP score thresholds, White students make up a larger proportion while Black and Hispanic students make up smaller proportions of included prospects when filtering for both GPA and AP relative to filtering for these individually. For example, White students make up 49% of included prospects when filtering for GPAs greater than or equal to 3.0 in combination with an AP score of 1 in any subject exam, whereas Hispanic and Black students make up 17% and 21%, respectively. Hispanic and Black student proportions decline as AP thresholds increase. This decline is most significant for Black students, which result in less than 1% of Black students making up included prospects when filtering for GPAs greater than or equal to 3.0 in combination with an AP score of 5. Moreover, these racial disparities are greater than when filtering for similar thresholds for GPA (Figure 7) and AP score (Figure 6) individually. The bottom panel of Figure 13 suggest similar results are evident when combining a GPA filter greater than or equal to 3.0 and an AP STEM exam filter.

7 Discussion

Prior scholarship on recruiting (e.g., Author, XXXXd) assumes that recruiting is done by individual colleges and universities. Universities identify prospective students by purchasing student lists, but prior research has not investigated how student list products structure the connection between universities and prospective students. We ask, what is the relationship between student list search filters and the racial composition of students who are included versus excluded in student lists purchased from College Board? We develop a conceptual framework about structural racism in algorithmic products by drawing from sociology and critical data studies. Structurally racist inputs are determinants of a selection device that are correlated with race because historically dominated racial groups have been historically excluded from the input (Hirschman & Bosk, 2020). We propose that several academic filters and geographic filters are structurally racist inputs. We assess propositions about the relationship between search filters and racial exclusion using a nationally representative sample of 9th graders from 2009.

Results for Proposition P1 suggest conditioning on test-taking is associated with racial disparities in included versus excluded prospects across SAT, PSAT, and AP exams. Test-takers are on average made up of larger proportions of White and Asian students and smaller proportions of Hispanic, Black, and American Indian/Alaska Native students. While some proportional differences between test-takers were modest, these proportions determine inclusion in the underlying College Board student list database and are then exacerbated by filtering across score thresholds in results for Proposition P2. When analyzing geographic filters, results for Proposition P3 suggest that included prospects have larger proportions of White students and smaller proportions of Hispanic and Black students as student list purchases filter on higher levels of zip code affluence. Additionally, results for Proposition P4 find that filtering at smaller levels of geography (zipcode) is associated with larger racial disparities between included versus excluded Hispanic and Black prospects in comparison to filtering at larger levels of geography (county).

Lastly, results suggest filtering on multiple criteria compound the effect of racial disparities between included versus excluded prospects. For example, we find that combining multiple academic filters such GPA and SAT/PSAT scores or GPA and AP scores leads to larger proportions of White students and smaller proportions of Black and Hispanic students within included prospects. Moroever, racial disparities between included versus excluded prospects are generally larger when combining multiple academic filters than when filtering at similar thresholds for any one filter individually. Similarly, orders that combine academic filters (GPA, SAT, PSAT) with zip code lead to lower proportions of Hispanic and Black students within included prospects across all levels of affluence and at greater disparities (relative to excluded prospects) than when filtering for zip code alone.

These results have policy implications for federal regulatory agencies concerned with consumer protection and equality of opportunity. Consider zip code filters. Given the history of racial segregation, there is no equality of opportunity rationale for products that enable universities to target particular zip codes. Over the last decade, the Federal Trade Commission (FTC) has become concerned about algorithmic products that "categorize consumers in ways that can result in exclusion of certain populations" (Federal Trade Commission, 2016, p. 9). The FTC enforces the FTC Act, which applies to all organizations engaged in interstate commerce.

Section 5 of the FTC Act prohibits "unfair" practices, defined as practices that meet three criteria: (1) causes substantial harm to consumers; (2) harm cannot be reasonably avoided; and (3) harm not outweighed by benefits to other consumers and to competition (FDIC, 2018). Zip code filters may cause substantial harm to consumers (criterion #1) because students who live in nearby non-targeted zip codes are excluded from college access opportunities. Consumers cannot reasonably avoid the injury (criterion #2) because they cannot easily move to a different zip code. The benefit to targeted consumers may not outweigh the harm to excluded consumers (criterion #3).

This manuscript is the first word on student list products, not the last word. Other filters may satisfy the FTC unfair practices criteria more unequivocally than zip code. Future research should examine filters based on predictive analytics, which model past cases to make predictions about future cases. 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. 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.

Another topic for future research is demographic search filters, which allow universities to target prospects by race, ethnicity, gender, and first-generation status. The equity rationale is that these filters facilitate access for underrepresented populations, particularly in a post affirmative action landscape. However, analyses by Author (XXXXb) found that purchases that filtered for underrepresented racial/ethnic groups often disproportionately targeted students from affluent, predominantly white schools and communities. Additionally, "women in STEM" purchases yielded profound racial and socioeconomic inequality.

In addition to empirical analyses, legal scholarship informs how regulatory agencies interpret the law. For example, Lawler & Dold (2021) argues that the Consumer Financial Protection

Bureau (CFPB) has regulatory authority over for-profit colleges because organizations that provide financial advisory services to consumers seeking loans – the activities of any financial aid office – are "covered persons" under the Consumer Financial Protection Act (CFPA). Similarly, legal scholarship can inform how the FTC and the CFPB intepret regulatory authority over student list vendors and products. One issue is whether and how student list vendors can be regulated as "consumer reporting agencies," which are regulated by the Fair Credit Reporting Act and the CFPA. A consumer reporting agency is an entity that sells information about prospective consumers that leads to the extension of credit (i.e., loans) (15 U.S.C §1681a). Student list vendors may qualify as consumer reporting agencies because of the systematic link between student lists and student loans. That is, the first stage of the enrollment funnel is to identify "leads" by purchasing student lists and the last stage is convert admits to enrolled students by offering financial aid packages.

The broader contribution of this manuscript is to motivate critical education policy research that focuses on third-party products and vendors. The majority of policy research in education analyzes students, schools, or universities, often in relation to federal, state, or local policies. Scholarship from critical data studies and sociology shows that structural racism is "a feature, not a bug" of digital platforms (Benjamin, 2019; Hicks, 2017; Noble, 2018) because racial exploitation is the defining feature of capitalism (Robinson, 2000) and the defining feature of platform capitalism (Cottom, 2020). By contrast, Nichols & Garcia (2022) observes that scholarship on technology and education is dominated by technocratic analyses of instruction and student learning outcomes. The nascent "platform studies in education" literature urges education research to follow the example of critical data studies and "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 platforms structure educational opportunity along racial, class, and geographic dimensions. We propose an empirical literature on third-party products and vendors in education that bridges scholarship on education policy and platform studies. This literature will incorporate structural theories of inequality and theories of organizational behavior from sociology and economics. Student list products represent a model topic for this literature.

One thread within this research agenda examines the business models of edtech platform capitalism (e.g., Komljenovic, 2022; Williamson, 2021). "Data rent" refers to "digital traces" created by users interacting with a platform (Sadowski, 2020), which often become the basis for new products. Drawing from Marx (1978), Sadowski (2019) develops the concept "data as capital" to describe how platforms monetize user-data. The formula $M - C - M'$ represents economic capital, whereby money M is invested to produce commodity C, which is sold for a larger amount of money M' (Marx, 1978). Student list products exemplify this process. Student list data are derived from the user-data of students laboring on a platform, whether that be taking a standardized assessment or searching for scholarships on a free college search engine. Processes that profit from student list data follow the formula for economic capital. College Board uses the cycle $M - C - M' - C - M''$, investing money (M) to create tests (C), which are sold to households for M' and also yield student list data (C), which are sold to universities (M'') looking for students. New entrants to the market for student list data (e.g., PowerSchool, EAB) add another link to the cycle. Instead of selling names at a price-per-prospect (e.g., $0.50) like College Board, they wrap proprietary databases of prospects within software-as-service products that recruit these prospects (e.g., Intersect, Enroll360), which are then sold to universities for an annual subscription.

Future critical policy research should also examine how college access is structured by vendors and consultancies in the broader enrollment management industry. Many universities depend on enrollment management consulting firms to recruit students (Author, XXXXa). In our public records data collection, roughly half the public universities outsourced student list buys to consulting firms (Author, XXXXb). These universities tended to be uninformed about who they were recruiting. Several enrollment management consultancies sell algorithmic products designed to make recommendations about list buys (Fire Engine RED, 2022; Ruffalo Noel Levitz, 2021). For example, Ruffalo Noel Levitz offers an algorithm that tells universities how many names to buy from each zip code (James Madison University, 2017). Beyond name buys, consultancies develop and implement strategy about digital advertising, direct mail, which high schools to visit, and tuition pricing and financial aid. To the extent that unviersities outsource enrollment management to consultancies, these consultancies substantially structure college access. However, extant scholarship on college access assumes that universities perform these functions in-house.

The enrollment management industry also structures "student success" in higher education and K-12. For example, EAB's Starfish student success software incorporates university administrative data, predicts student outcomes using past data, issues notifications when students get "off-track," and "make[s] student intervention easy and integrated" (EAB, 2022). A growing number of scholars are harnessing advances in machine learning to predict student success (e.g., Cardona, Cudney, Hoerl, & Snyder, 2022). Commercial student success products also utilize machine learning, but scholarship has not investigated the fairness of third-party predictive models sold to universities. Do these models use race/ethicity as an input? Do commercial student success platforms achieve higher graduation rates by pushing students out of certain majors?

Difficulty obtaining data is an obstacle to empirical scholarship on third-party vendors and products. Pasquale (2015) notes that "deconstructing the black boxes of Big Data isn't easy" because platform capitalism creates intentional barriers to inspection (p.6). Cottom (2020) argues that "administrative opacity is a deliberate strategy to manage regulatory environments. It shields organizations, both public and private, from democratic appeals for access and equity" (p. 443).

Student list products exemplify this opacity. College Board began selling student lists in 1972 (Belkin, 2019), but prior research never investigated student list products because few people know they exist and because of difficulty obtaining the data. We spent three years – years we would like back! – attempting to collect data about student list products by issuing public records requests to public universities (Author, XXXXb). We gained traction only after obtaining pro bono representation from four multinational law firms.

This manuscript suggests that investigating third-party products need not be so laborious. Author (XXXXb) assumed that quantitative analysis of College Board student list products required (1) order summary data (i.e., filter criteria) and (2) prospect-level student list data for each purchase. By contrast, this manuscript shows that analyses of student list products require (1) knowledge of product specifications and (2) student-level survey data containing variables necessary to recreate these product specifications. The analyses presented here additionally utilized order summaries collected via public records requests. However, obtaining order summaries is less daunting than obtaining both the order summary and the associated prospect-level data for each purchase.

Future research can investigate third-party products by combining rich NCES longitudinal survey data with methods from investigative journalism (e.g., Feathers, 2022). Consider commercial "student success" products like EAB's Starfish. First, researchers can learn about product specifications from internet searches by attending trade shows (e.g., NACAC) where vendors peddle their wares. State contract databases, for example the Illinois Procurement Bulletin, show which public universities purchased Starfish. Additional information about product specifications can be obtained by issuing public records requests to universities that purchased a Starfish contract (the best use of public records requests is obtaining contracts and product documentation). Second, use NCES survey data to recreate – or approximate – the input measures utilized by the product. Third, recreate the analytic approaches utilized by the product. One caution, algorithimic products often facilitate targeting by geographic locality, but NCES survey sample sizes are often too small for analyses of particular states or metropolitan areas.

The payoff for developing this critical policy literature is great, and so is the cost of inaction. Third-party providers do not want to be the object of research because scrutiny from scholars will lead to scrutiny from regulators, which may disrupt profitable practices (Cottom, 2020). Increasingly, third-party providers perform core functions of schools and universities (Komljenovic, 2022; Nichols & Garcia, 2022). If researchers continues to ignore these products, then policy research will have diminishing influence on core functions of schools and universities. As conservative courts challenge progressive education policies like affirmative action, policy research should go on the offensive by applying theory about structural mechanisms to investigate structural racism by third-party products and vendors.

In higher education, third-party providers now dwarf the for-profit college market. Nevertheless, the Higher Education Act (HEA) – enforced by the US Department of Education – regulates for-profit Title IV institutions, but remains agnostic about "third-party servicers" (aside from lenders and guaranty agencies). For example, responding to concerns about incentive-based compensation for online program management (OPM) companies, the Department of Education (2011) argued that tuition sharing with third-party vendors is not problematic because enrollment goals are determined by the institution, not the vendor.[8]

Therefore, developing a critical policy literature on third-party vendors/products demands that researchers be "price-makers" rather than "price-takers" when it comes to which issues demand policy attention. Instead of doing research that fits within the constraints of federal education policy, do research that shifts the focus of federal policy. Given the narrow focus of the HEA and the Department of Education, this research agenda should target the Federal Trade Commission, the Consumer Finance Protection Bureau and other agencies that enforce laws concerned with equality of opportunity for consumers. This shift in target audience requires researchers to learn more about these regulatory agencies, the laws they enforce, and to develop relationships with key staff. This new research focus represents a "paradigm shift" in education policy research, as opposed to "normal science" (Kuhn, 1962). This paradigm shift will be well remunerated with policy impact and scholarly productivity.

[8] US Department of Education (2011) states that, "the independence of the third party (both as a corporate matter and as a decision-maker) from the institution that provides the actual teaching and educational services is a significant safeguard against the abuses the Department has seen heretofore. When the institution determines the number of enrollments and hires an unaffiliated third party to provide bundled services that include recruitment, payment based on the amount of tuition generated does not incentivize the recruiting as it does when the recruiter is determining the enrollment numbers" (p.11)

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9 Tables

Table 1: Top filter combinations used in College Board orders purchased purchased by 14 public universities

Filters	Count	Pct	Cum count	Cum pct
HS grad class, GPA, SAT, Zip code	206	24.8	206	24.8
HS grad class, GPA, PSAT, Zip code	145	17.5	351	42.3
HS grad class, GPA, SAT, PSAT, Rank, State, Race	39	4.7	390	47.0
HS grad class, SAT, State	38	4.6	428	51.6
HS grad class, GPA, SAT, PSAT, Zip code	28	3.4	456	54.9
HS grad class, PSAT, State	28	3.4	484	58.3
HS grad class, GPA, SAT, State	23	2.8	507	61.1
HS grad class, GPA, PSAT, State, Race	20	2.4	527	63.5
HS grad class, PSAT, State, Low SES	20	2.4	547	65.9
HS grad class, GPA, PSAT, State	19	2.3	566	68.2
HS grad class, GPA, AP score, Geomarket	15	1.8	581	70.0
HS grad class, PSAT, Geomarket	14	1.7	595	71.7
HS grad class, GPA, SAT, PSAT, State, Segment, Gender	13	1.6	608	73.3
HS grad class, SAT, State, College size	11	1.3	619	74.6
HS grad class, SAT, State, Low SES, College size	11	1.3	630	75.9
HS grad class, GPA, SAT math, SAT reading/writing, State, Segment	10	1.2	640	77.1
HS grad class, PSAT, State, Segment	10	1.2	650	78.3
HS grad class, PSAT, Geomarket, Low SES	9	1.1	659	79.4
HS grad class, SAT, Geomarket	9	1.1	668	80.5
HS grad class, GPA, AP score, State	8	1.0	676	81.4

Table 2: 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				
SAT Test-Taker	7,910	1,860,677	54,277	55.6
SAT Non-Test-Taker	8,610	2,326,689	54,249	44.4
PSAT Test-Taker	4,780	3,086,739	51,247	73.7
PSAT Non-Test-Taker	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

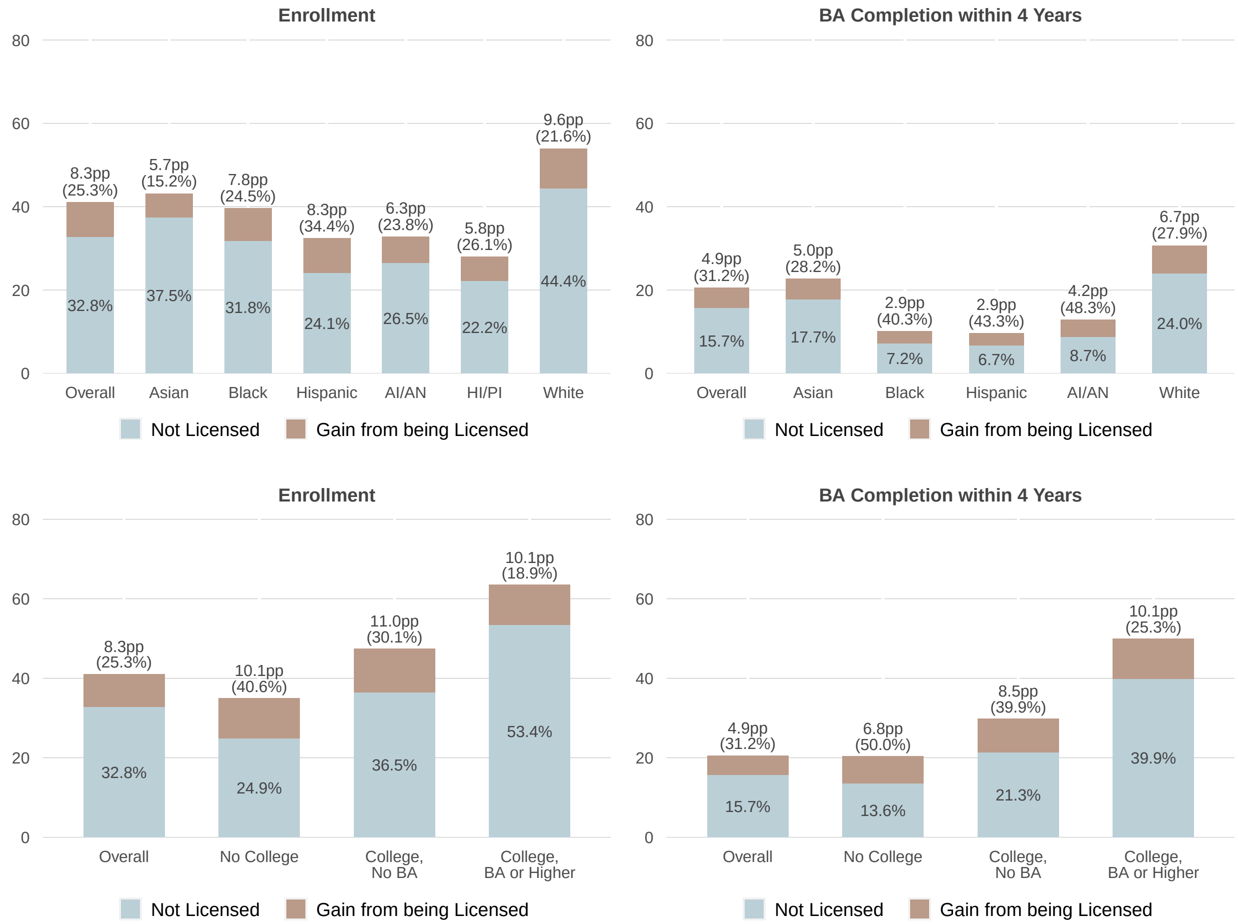
* Unweighted sample sizes rounded to nearest 10 per NCES restricted data license regulations

Table 3: Test Taker Differences in Proportion

	Included	Excluded	Difference	Lower CI	Upper CI
SAT					
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
PSAT					
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

10 Figures

Figure 1: Student Search Service and four-year college enrollment/completion



Notes: AI/AN = American Indian or Alaska Native. HI/PI = Hawaiian or Pacific Islander. Sample for enrollment outcomes is all SAT takers in the 2015–2018 high school graduation cohorts. Sample for completion outcomes is students in the 2015–2016 cohorts. Results are estimated from regressions that include student-level controls for: sex, race/ethnicity, SAT score, parental education level, last Student Search Service opt-in status, graduation cohort, and high school fixed effects. All differences between licensed versus non-licensed students are statistically significant at the 1% level.

Figure 2: The enrollment funnel

Figure 3: Filters used in College Board orders purchased by 14 public universities

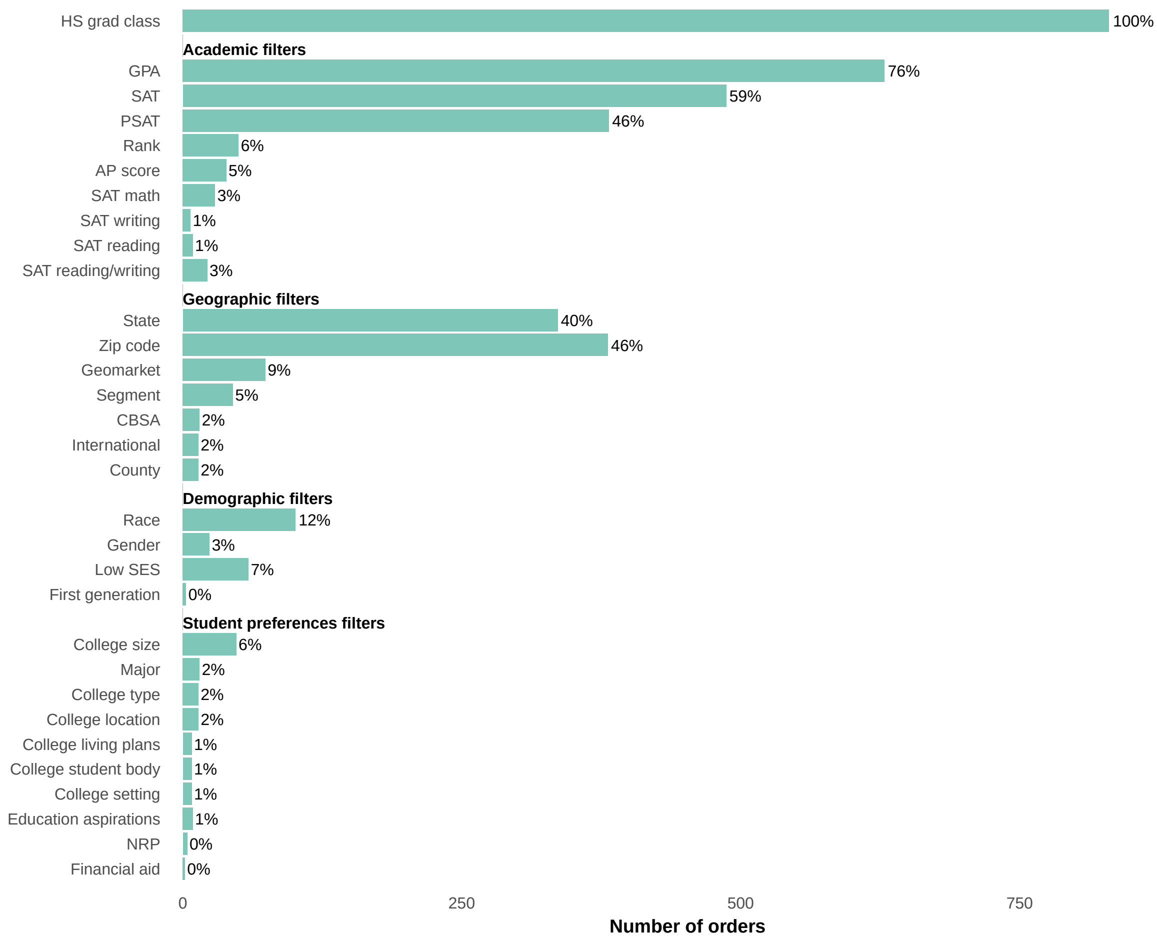


Figure 4: Test Takers Across SAT, PSAT, and AP Assessments

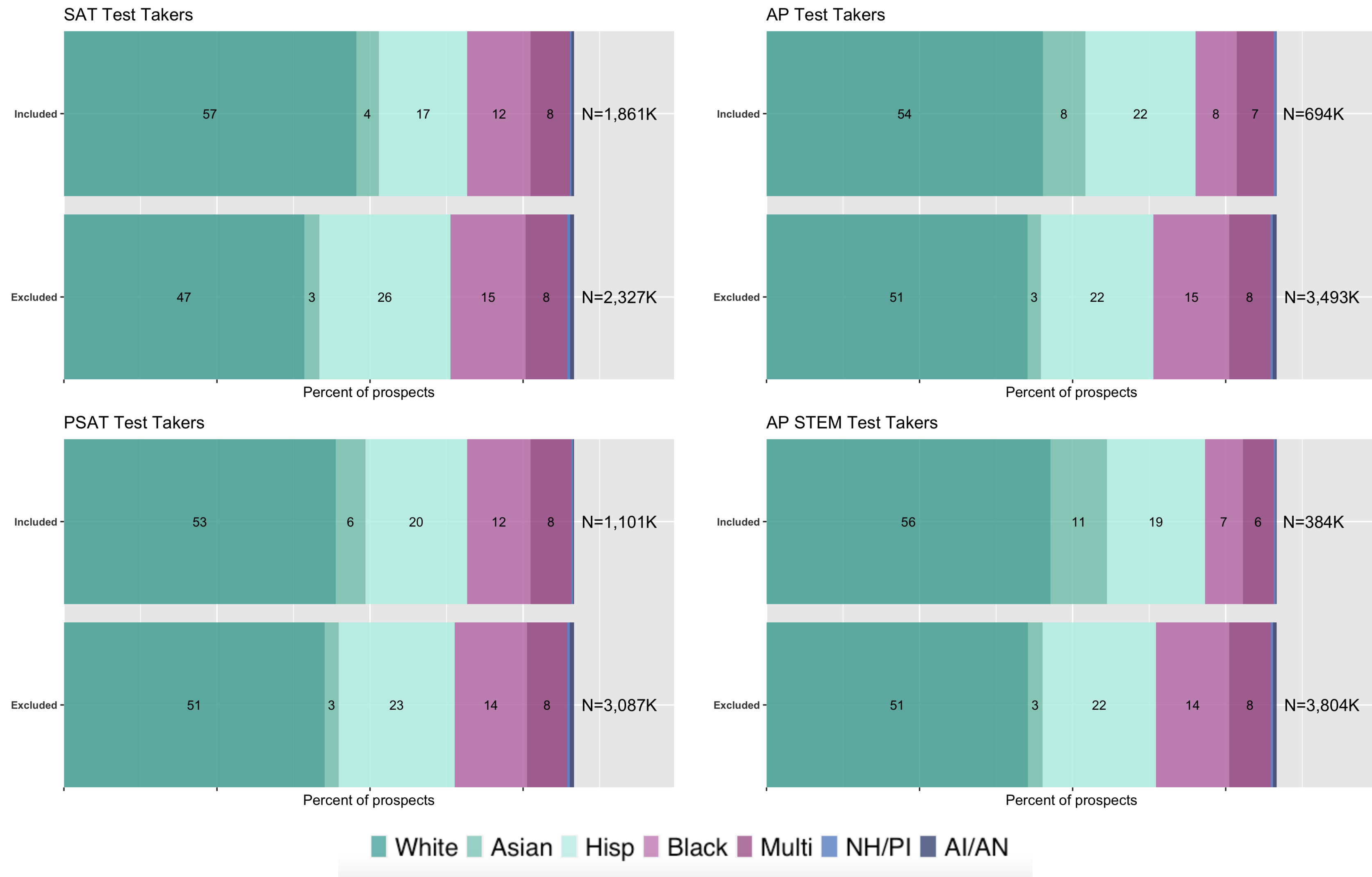


Figure 5: SAT and PSAT Filters Across Thresholds

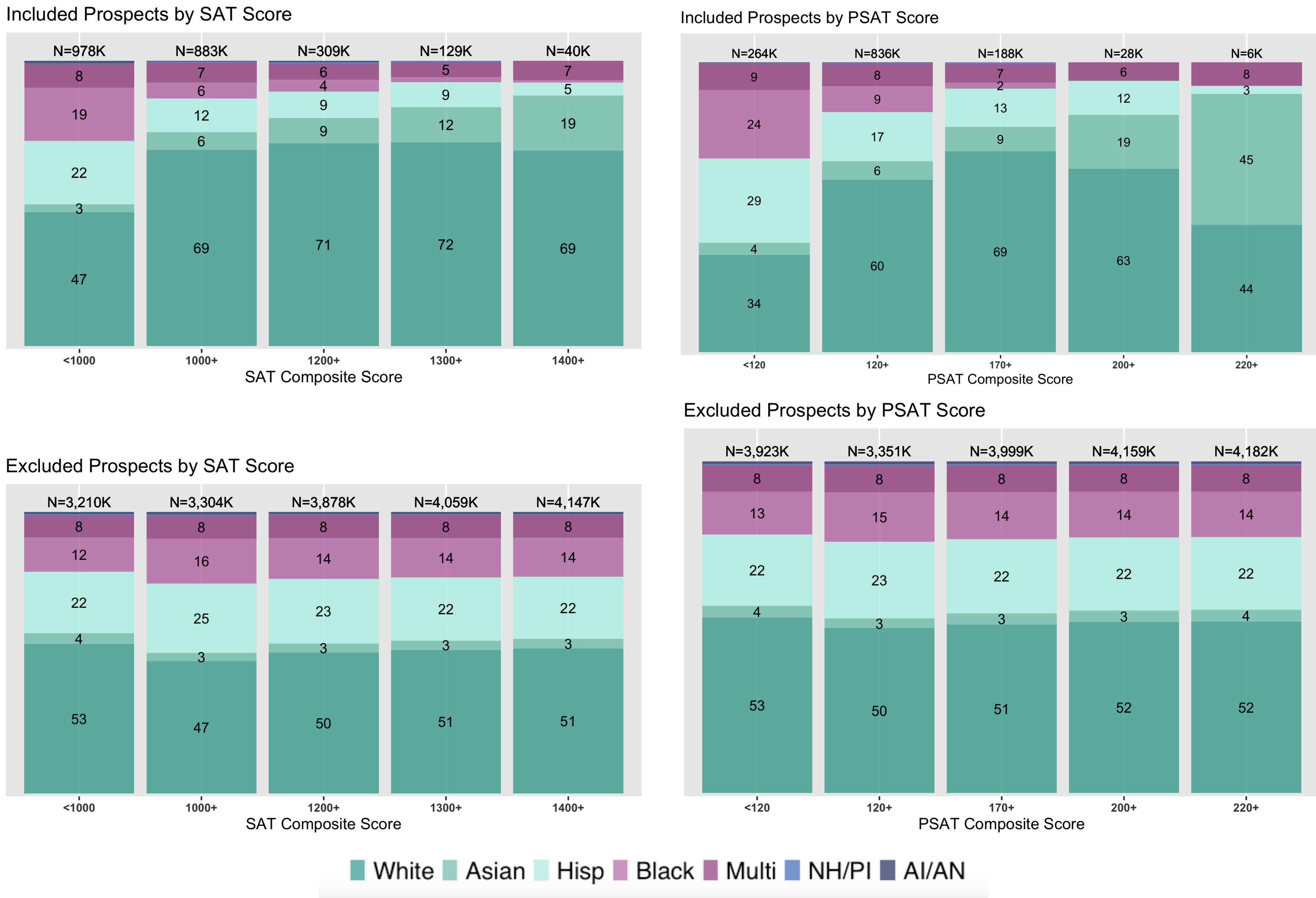


Figure 6: AP Filter Across Thresholds

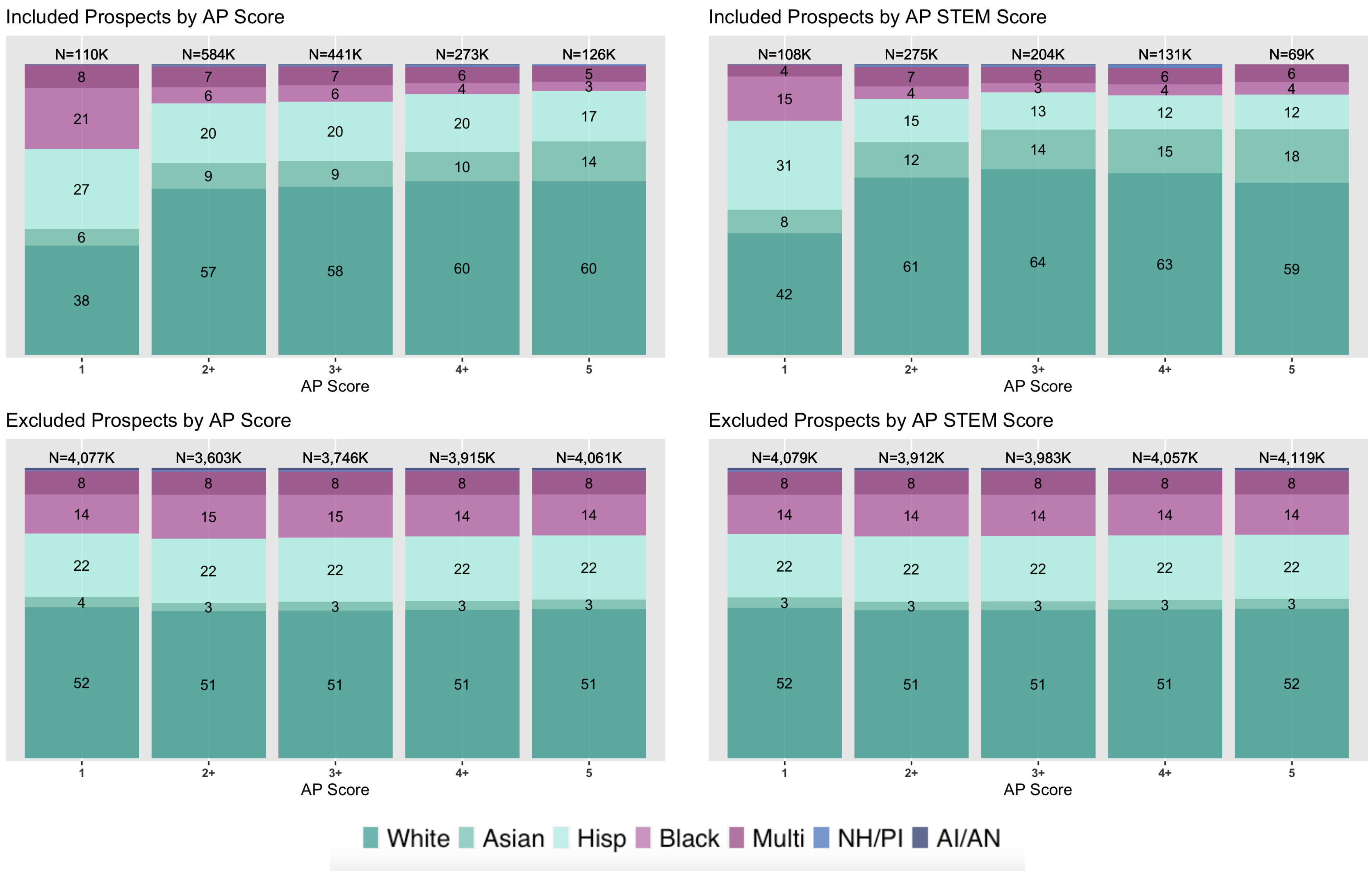


Figure 7: GPA Filter Across Thresholds

Figure 8: Zip Code Filter Across Affluence Percentiles

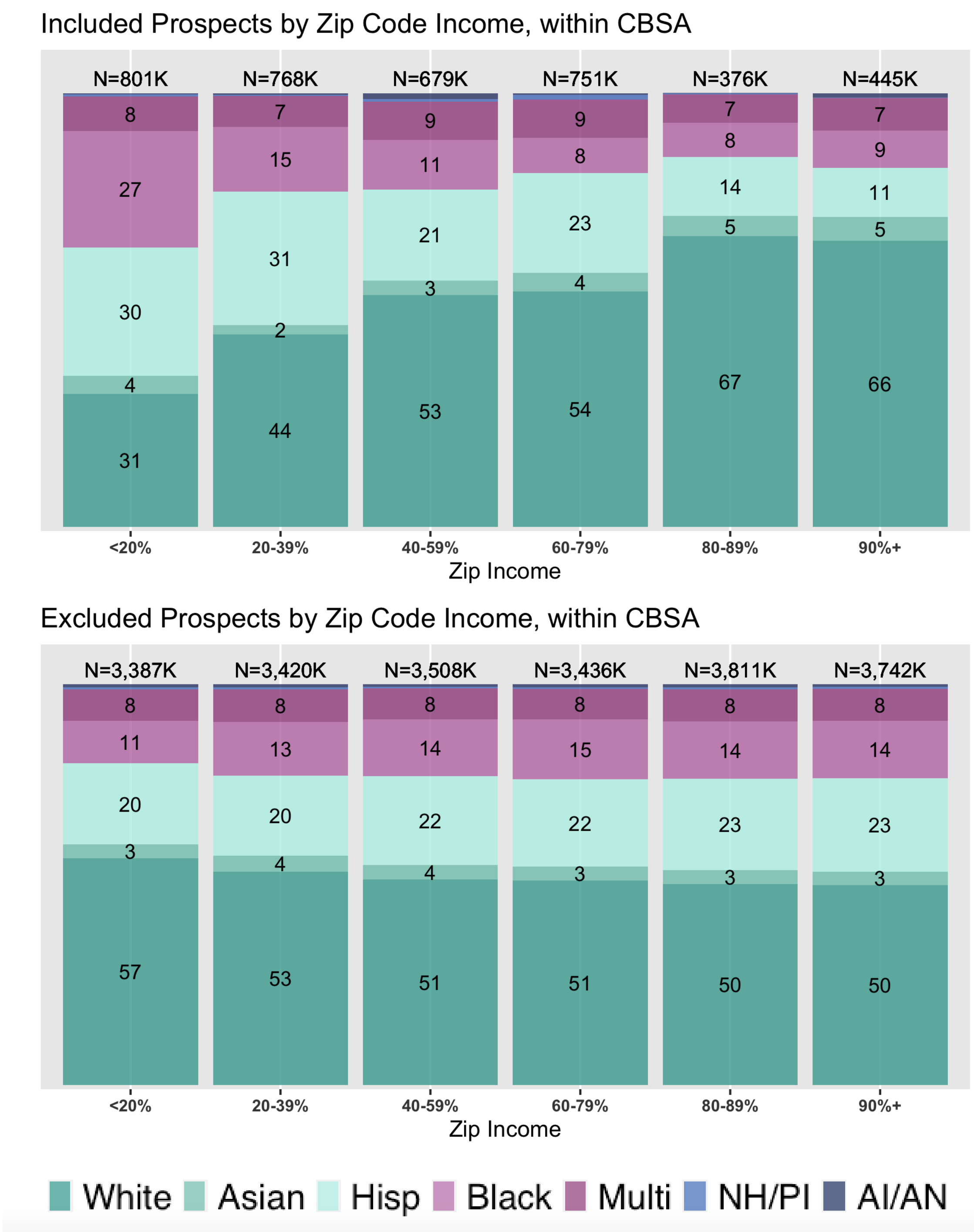


Figure 9: Zip Code Filter Across Affluence Percentiles for Los Angeles and New York

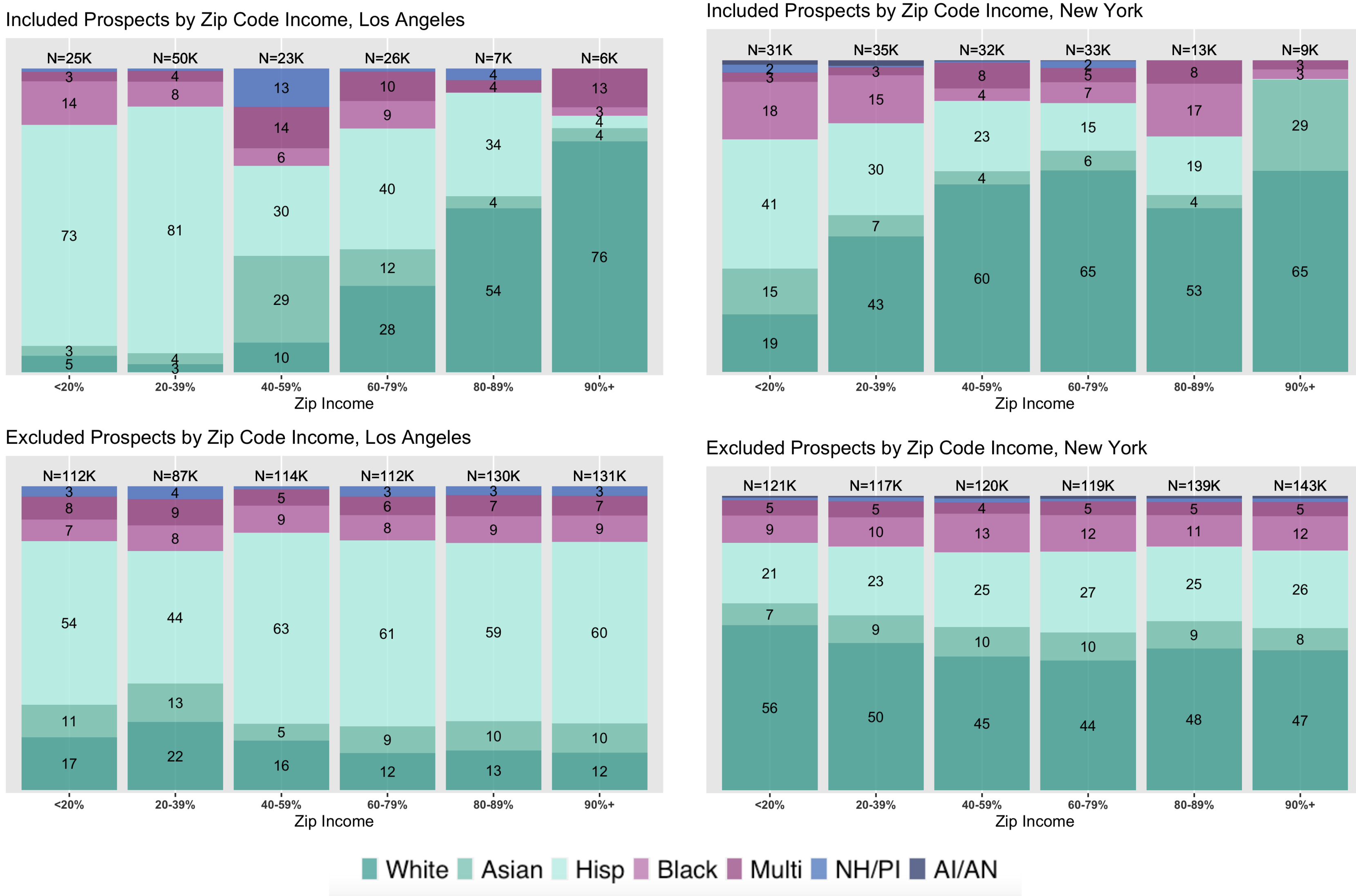


Figure 10: Zip Code and County Filters Across Affluence Levels

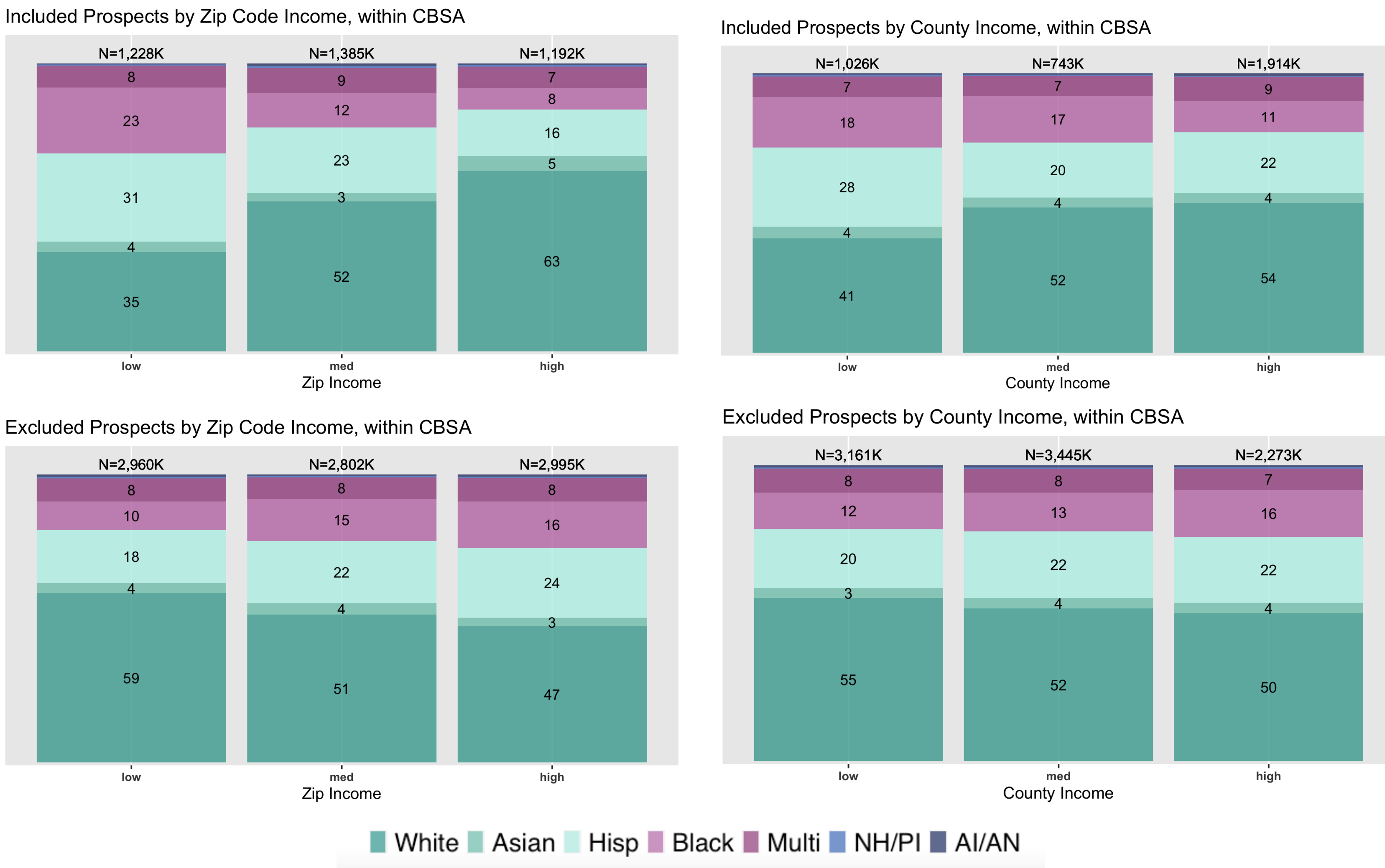


Figure 11: Academic and Geographic Combination: GPA (3.0+) and SAT or PSAT (across score thresholds)

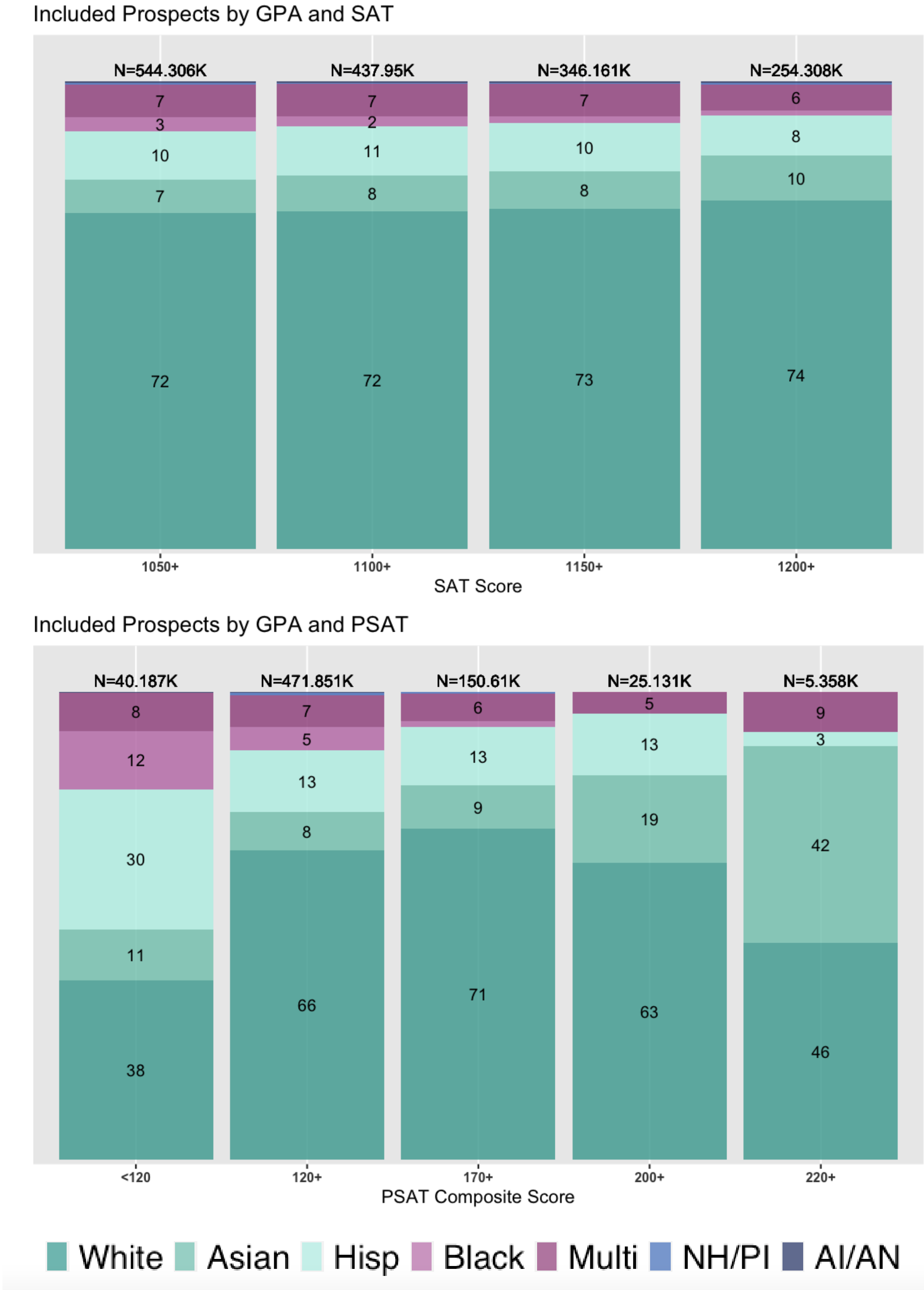


Figure 12: Academic and Geographic Combination: GPA (3.0+), PSAT (150+) or SAT (1050+), and Zip (across income thresholds)

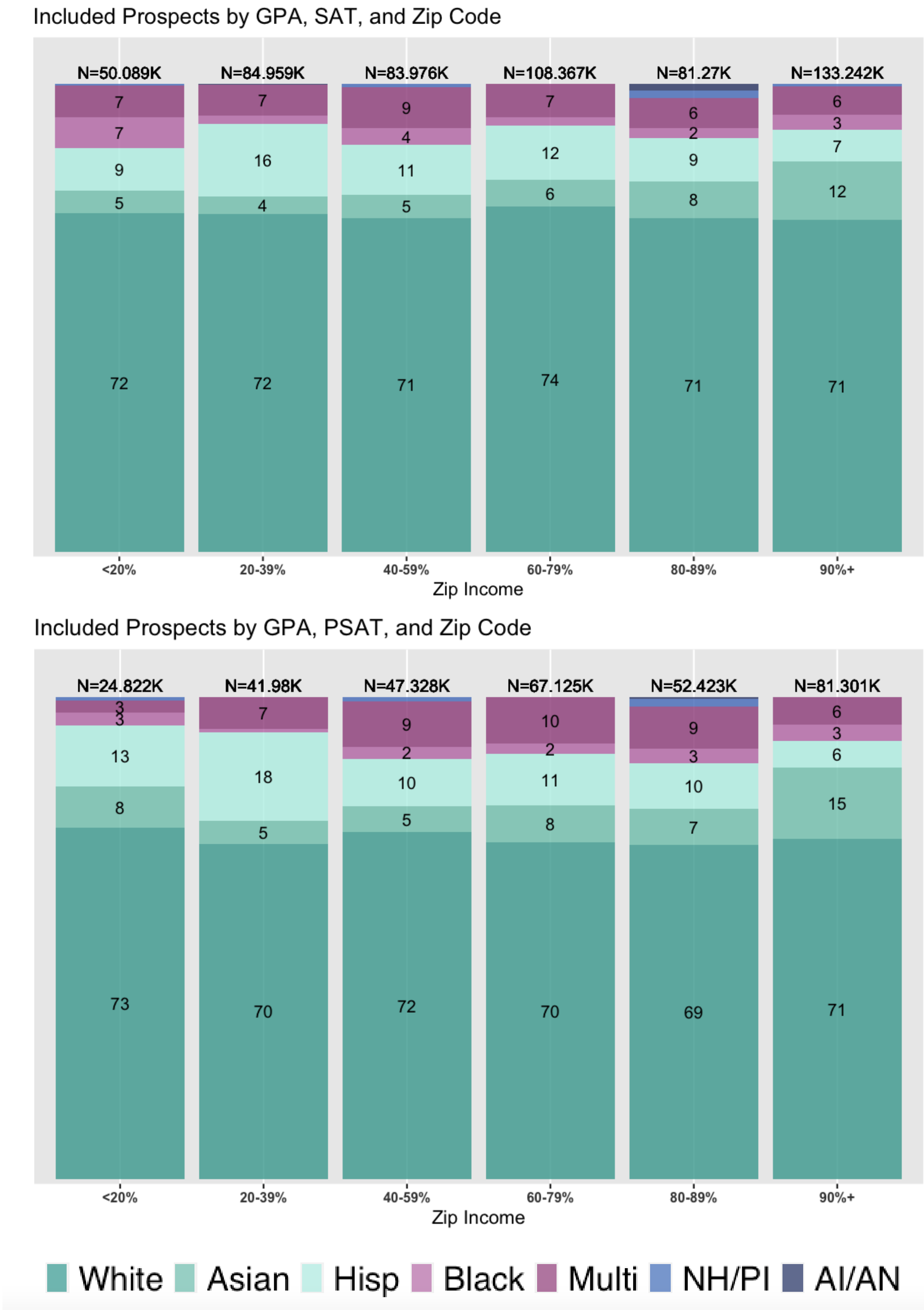
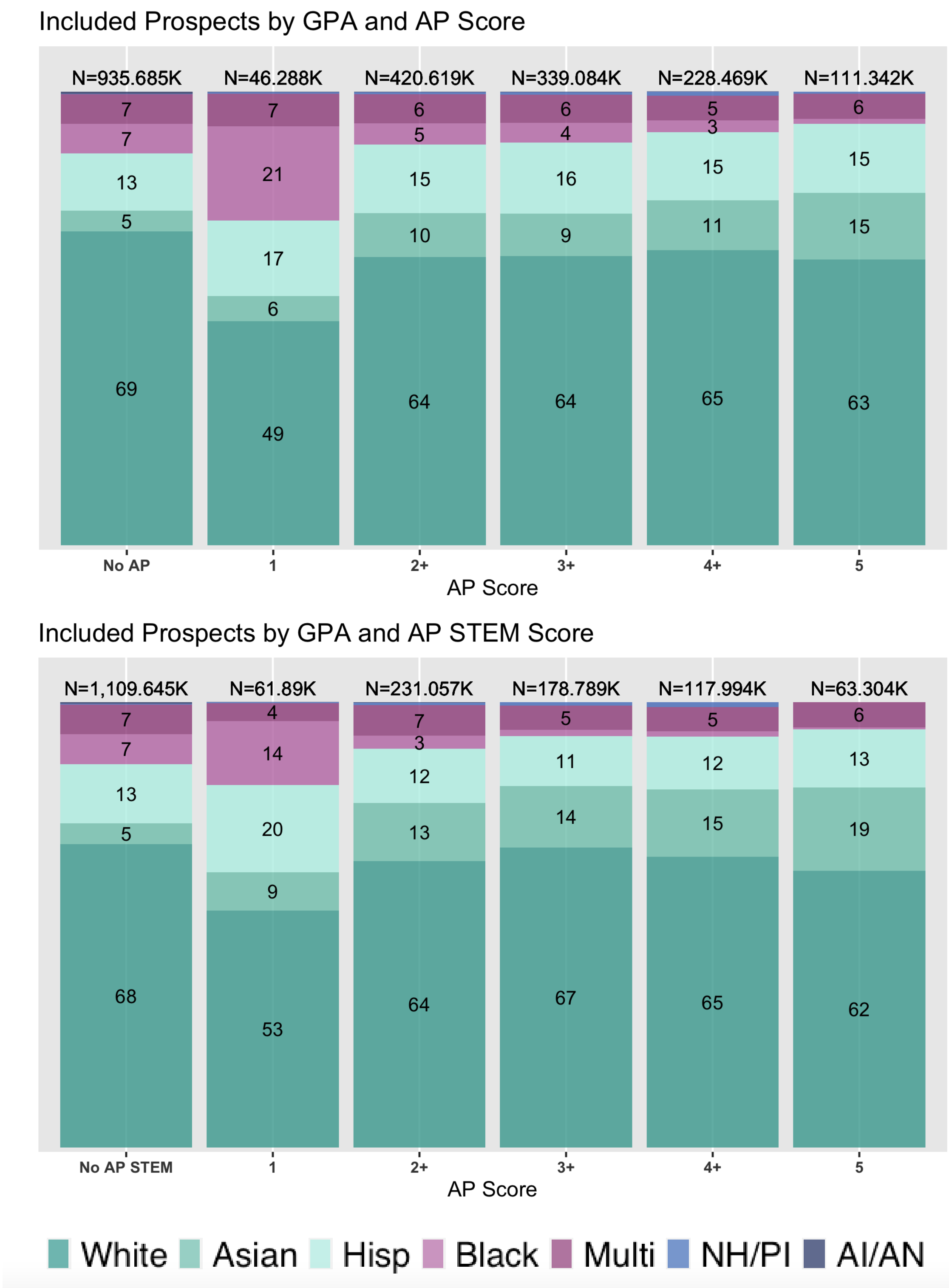


Figure 13: Academic and Geographic Combination: GPA (3.0+) and AP (acrossscore thresholds)



11 Online Appendix

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

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
SAT							
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
PSAT							
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***

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

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
Affluence Percentile							
Less than 20%	-0.260***	0.008***	0.094***	0.163***	0.000	0.001***	-0.005***
20-39%	-0.089***	-0.018***	0.108***	0.015***	-0.010***	-0.002***	-0.003***
40-59%	0.021***	-0.002***	-0.012***	-0.028***	0.010***	0.001***	0.009***
60-79%	0.031***	0.010***	0.011***	-0.068***	0.012***	0.007***	-0.003***
80-89%	0.169***	0.011***	-0.091***	-0.065***	-0.015***	-0.003***	-0.006***
Greater than 90%	0.160***	0.020***	-0.120***	-0.056***	-0.006***	-0.003***	0.004***

Table 6: Zip and County Proportion Differences in Included vs. Excluded across Race/Ethnicity

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
Zip							
Low Income	-0.242***	0.000	0.123***	0.129***	-0.005***	-0.001***	-0.005***
Moderate Income	0.007***	-0.010***	0.012***	-0.026***	0.011***	0.002***	0.003***
High Income	0.154***	0.023***	-0.083***	-0.085***	-0.008***	0.001	-0.001***
County							
Low Income	-0.141***	0.008***	0.084***	0.059***	-0.008***	0.003***	-0.004***
Moderate Income	0.004***	0.000	-0.027***	0.035***	-0.010***	0.001	-0.002***
High Income	0.037***	0.000	-0.005***	-0.047***	0.014***	-0.001***	0.002***

Table 7: GPA and PSAT/SAT Score Threshold Proportion Differences in Included vs. Excluded across Race/Ethnicity

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
SAT							
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***
PSAT							
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

Table 8: GPA, PSAT/SAT, and Zip Code Proportion Differences in Included vs. Excluded across Race/Ethnicity

	White	Asian	Hisp	Black	Multi	NH/PI	AI/AN
SAT (1050+)							
Less than 20%	0.098***	0.028***	-0.077***	-0.056***	0.016***	-0.002***	NA
20-39%	0.166***	0.031***	-0.087***	-0.095***	-0.012***	0.003***	-0.006***
40-59%	0.252***	0.020***	-0.117***	-0.113***	-0.032***	NA	-0.005***
60-79%	0.129***	0.045***	-0.041***	-0.129***	-0.008***	0.007***	-0.004***
80-89%	0.269***	0.067***	-0.189***	-0.120***	-0.017***	NA	NA
Greater than 90%	0.230***	0.058***	-0.174***	-0.109***	-0.007***	0.002***	-0.002***
PSAT (150+)							
Less than 20%	0.172***	0.023***	-0.084***	-0.117***	0.013***	0.001	NA
20-39%	0.125***	0.050***	-0.057***	-0.108***	-0.007***	0.006***	NA
40-59%	0.250***	0.029***	-0.149***	-0.104***	-0.018***	-0.005***	-0.004***
60-79%	0.101***	0.049***	-0.051***	-0.121***	0.020***	0.009***	NA
80-89%	0.240***	0.091***	-0.179***	-0.119***	-0.023***	NA	NA
Greater than 90%	0.216***	0.082***	-0.157***	-0.106***	-0.024***	NA	NA

Table 9: 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