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," which target individual prospects by mail, email, and on social media.

Recent research suggests that student lists are surprisingly important for college access – and degree completion – for millions of students each year. Jessica Howell, Hurwitz, Mabel, & Smith (2021) compared SAT test-takers who opted into the College Board Student Search Service – allowing accredited institutions to "licence" their contact information – and test-takers who opted out, after controlling for covariates (for a similar analysis of ACT's Educational Opportunity Service see Moore (2017)). Figure 1 reproduces the main results. For students with the same values of SAT score, parental education, race/ethnicity, sex, graduation year, and who attended the same high school, 41.1% of students who participated in Search attended a 4-year college compared to 32.8% of students who opted out, representing an 8.3 percentage point difference and a 25.3 (`=(41.1-32.8)/32.8`) percent change in the relative probability of attending a 4-year college. Participating in Search was associated with a larger percent change in the probability of attending a 4-year institution for students who identified as Black (24.5%) and Latinx (34.4%) than it was for students who identified as White (21.6%) and this percent change was also larger for for students whose parents did not attend college (40.6%) than it was for students whose parents had a BA (18.9%).

Despite the importance of student lists for college access, recent reports by *TICAS* argue that student list products systematically exclude underrepresented student populations in two ways [CITE]. The first source of exclusion is which prospective students are in the underlying database. Historically, student list products sold by College Board and ACT exclude non test-takers, but rates of test-taking differ by race and class. Second, several "search filters" (e.g., zip code, AP score) used to control which prospect profiles are purchased facilitate the effecient exclusion of students from communities of color and low-income communities. [ONE SENTENCE ON TEST-OPTIONAL AND FOR-PROFIT PROVIDERS OF STUDENT LISTS TAKING OVER?]

Prior scholarship assumes that recruiting is something done by individual universities [CITE], motivating policies that incentivize or regulate (e.g., nonresident enrollment caps) university behavior. In reality, the recruiting behavior of universities is structured by products sold by third-party vendors and consultancies in the enrollment management industry (Jaquette, Salazar, & Martin, 2022). The nascent "platform studies in education" literature observes that digital platforms increasingly perform core functions of schools and universities (Komljenovic, 2022a; Nichols & Garcia, 2022). This literature calls for critical, empirical scholarship that informs policy regulations about the role of big tech and edtech in education (Kerssens & Dijck, 2022; Ben Williamson, Gulson, Perrotta, & Witzenberger, 2022). In contrast to the robust scholarship about racial discrimination within the field of critical data studies (e.g., Benjamin, 2019; Noble, 2018), few studies within education research investigate how platforms that structure educational opportunity exclude along the dimensions of race, class, and geography. This study analyzes student list products sold by College Board. We ask, what is the relationship between student list search filters (e.g., test score range, zip code) and the characteristics of students who are included vs. excluded in student lists purchased from College Board?

We develop a conceptual framework about the relationship between search filters and exclusion by drawing from recent scholarship in the sociology of race about algorithmic products. Algorithms are instructions written in code (Burrell & Fourcade, 2021). 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 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. 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. We conceptualize several "geographic" and "academic" search filters as structurally racist inputs. For example, prospects may be filtered by zip code, but zip codes are correlated with race because of residential segregation. Prospects may be filtered by AP test scores, but who attends schools with access to AP curricula? [say geodemographic?]

We address the research question using data from the High School Longitudinal Study (HSLS:09), which follows a nationally representative sample of 9th graders from 2009. We reconstruct the search filters and filter thresholds from the College Board Student Search Service product. We then simulate simulate student list purchases commonly observed and theoretically motivated search filters with the goal of understanding the racial, socioeconomic, and geographic characteristics of students who are included versus excluded from student list purchases. [RESULTS SHOW. . .]

The discussion section addresses policy implications and scholarly contribution. We argue that several search filters satisfy the criteria of "unfair practices" of the Federal Trade Commission (FTC) Act. Additionally, because of the systematic link between student lists and student loans, student list vendors may meet the criteria of Consumer Reporting Agencies, which are regulated by the FTC [TRUE?] and the Consumer Finance Protection Bureau (CFPB).

Our broader contribution is to policy research on college access. Extant research analyzes students, schools, or universities, often in relation to local, state, or federal policies. Although federal higher education policies often focus on for-profit colleges, third-party for-profit vendors now dwarf direct providers. We propose a critical, empirical research program on college access that focuses on organizations and products in the edtech sector. Like student list data, most digital platforms in education are derived from the user-data of students laboring on platforms. What these platforms do with student data is opaque, because obfuscation is a deliberate strategy to avoid regulation (Cottom, 2020). Scholarship from critical data studies shows that structural racism in digital platforms is "a feature, not a bug" because racial exploitation is the defining feature of capitalism (Benjamin, 2019). As courts challenge progressive college access 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. Given the narrow scope of the Department of Education and the Higher Education Act (HEA), this research should target the FTC, the CFPB, and other agencies that serve equality of opportunity for consumers.

2 Background: The Student List Business

2.1 Situating Student 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 – composed of household savings and grants and loans from federal, state, and private sources – 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 have a financial incentive to provide access to students. Additionally, universities pursue some mix mix of broad enrollment goals (e.g., academic profile, racial diversity), while also meeting the needs of various campus constituencies (e.g., College of Engineering needs majors, marching band needs players) (Stevens, 2007). Universities cannot realize these goals solely from prospects who contact the university on their own. They must find prospects who can convinced to apply. However, universities don't know who they are, where they are, or how to contact them. Student lists overcome the problem faced by universities, providing the contact information of prospects who satisfy their criteria.

The "enrollment funnel" – depicted in in Figure 2 – is 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, taking a virtual tours that records IP address). 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 (e.g., McPherson & Schapiro, 1998).

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 data provided by university 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%).[1]

[1]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).

2.2 The Market for Student List Data

Historically, the student list business has been dominated by College Board and ACT. In the 21st Century, student lists have been central a surprising level of dynamism in the broader enrollment management industry. Jaquette et al. (2022) describes key dynamics that shaped the contemporary market for student list data. The first dynamic is the centrality of enrollment management consulting firms to the student list business. Although universities are the paying customers of student list products, many universities outsource student list purchases to 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 followed by concentration. 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 one enrollment management consulting firm acquired a competitor (e.g., e.g., RuffaloCODY acquired Noel-Levitz in 2014) [CITE]. Vertical transformations 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. 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 predicted probability of enrolling) based on statistical models. Additionally, 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 to the college entrance exam. 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 ceded by College Board and ACT.

3 Literature Review

We position our scholarly contribution as a bridge between two literatures. First, we review scholarship that informs the nascent "platform studies in education" literature. Second, we review empirical scholarship on recruiting, focusing on scholarship from sociology.

3.1 Platform Studies in Education

Digital platforms (e.g., Uber, Coursera, Naviance) are intermediaries for exchange that coordinate market transactions and create new markets (Sadowski, 2020). Platforms are also the "ground on which all the user activity happens, allowing the platform to record everything happening in it" (Komljenovic, 2021, p. 322). An emerging literature examines digital platforms in education (e.g., Kerssens & Dijck, 2022; Komljenovic, 2022a; Nichols & Garcia, 2022). This literature consciouslly draws from a multidisciplinary, transnational set of literatures on "platform studies" (e.g., Benjamin, 2019; Noble, 2018; Sadowski, 2019).

One thread of platform studies deconstructs the "platform capitalism" business model. Platform capitalism is often called "rentier capitalism" because the dominant business model generates profit by charging customers "rent" – as in the rent a tenant pays a landlord – for the right to use the platform without transferring ownership rights to the customer (Sadowski, 2020). Monetary rent refers to money a customer pays to an organization for access to digital products, for example a university pays annual subscription fees to Elsevier for access to academic journals (Komljenovic, 2021). Data rent refers to "digital traces" that platform users create by interacting with the platform (e.g., personal information they submit, interactions on the platform) (Komljenovic, 2021). Digital platforms gain ownership over user data via terms-of-use agreements. Drawing from Marx (1978), Sadowski (2019) develops the concept "data as capital," to describe how platforms monetize user-data, which may be used to improve the platform or may become the basis for a new platform.

Another thread of platform studies, emerging from critical data studies, examines how digital platforms reproduce structural inequality (Benjamin, 2019; e.g., Noble, 2018; O'Neil, 2016). Noble (2018) shows that the results of search algorithms reflect racist ideologies of people on the internet and the profit imperative of adverters that capitalize on these ideologies. Benjamin (2019) develops *race critical code studies* and attendant concepts. For example, "discriminatory design" is the process embedding structural inequality in platform algorithms, for example, by scoring customers based on an input that people of color have been excluded from. The concept "technological determinism" describes how biased algorithms affect society by amplying the effects of structurally racist inputs.

Student list products are exemplars of platform capitalism that reproduce structural inequality. Student list data are extracted from the user-data of students laboring on platforms to prepare for college (e.g., taking the SAT) or search for college. Terms-of-use agreements grant platforms ownership over these data. Following Sadowski (2019), College Board monetizes this commodity by licensing names to universities for roughly $0.50 per prospect. New entrants to the market (e.g., EAB, PowerSchool) 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. Student list products reproduce structural inequality because search filters used to target particular prospects – for example, filters for zip code and AP test scores – are themselves products of historical inequality in educational opportunity.

The Summer 2022 special issue of *Harvard Educational Review* sets the commitments and direction of the nascent "platform studies in education" literature. Nichols & Garcia (2022) reviews extant scholarship on technology within education research, observing that most scholarship focuses on technical questions about student learning outcomes and instructional practice. Napier & Orrick (2022, p. 207) states that, "platform studies scholars urge us to go beyond pedagogical and technical questions toward social, political, and economic critiques. Consistent with this call, a growing transnational literature examines the economic business models of platform capitalism in the education sector (e.g., Komljenovic, 2022b, 2022a; B. Williamson, 2021). Big tech and edtech companies profit by developing software systems – sold for an annual subscription – that perform core functions of education systems [E.G.,]. Other studies observe that, as education systems outsource core functions, digital platforms exert influence on organizational governance and education policy (Napier & Orrick, 2022; e.g., Ben Williamson et al., 2022).

We contribute to the platform studies in education literature. Most broadly, we contribute empirics to a literature that consists mostly of conceptual articles. More substantively, in contrast to scholarship from critical data studies (e.g., Noble, 2018), scholarship on education does not show how platforms structure educatonal opportunity along racial and class dimensions. Furthermore, while scholarship argues that digital platforms influence education policy (Kerssens & Dijck, 2022), extant scholarship falls short of analyses that show how platforms should be regulated.

3.2 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. Whereas scholarship from economics tends to analyze the effects of specific recruiting interventions (e.g., Andrews, Imberman, & Lovenheim, 2020; Miller & Skimmyhorn, 2018; Smith, Howell, & Hurwitz, 2021), scholarship from sociology tends to observe how recruiting happens "in the wild" so to speak. Our review focuses on scholarship from sociology and we identify a key blind spot, but one that is shared by scholarship from economics and the broader interdisciplinary field of education research.

Scholarship from sociology has analyzed recruiting from the perspective of students, high schools, and postsecondary institutions (e.g., Cottom, 2020; Holland, 2019; Posecznick, 2017; Salazar, Jaquette, & Han, 2021; Stevens, 2007). This literature primarily utilizes ethnographic or case-study designs, and often analyzes recruiting as part of a broader analysis of college access or enrollment management. Holland's (2019) analysis of pathways from high school to college exemplifies scholarship that engages with recruiting from the perspective of high school students (e.g., McDonough, 1997). Students from groups underrepresented in higher education were drawn to colleges that made them feel wanted because they felt "school counselors had low expectations for them and were too quick to suggest that they attend community college" (Holland, 2019, p. 97). These students were strongly influenced by marketing material and high school recruiting visits, including small-group representative visits and instant decision events. By contrast, affluent students with college-educated parents were less taken by such overtures and more concerned with college prestige.

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 (Jaquette, Han, & Castaneda, forthcoming). Stevens (2007) provides an ethnography of enrollment management at a selective, tuition dependent private college sensitive about rankings. 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 underqualified appicants into top colleges by exploiting colleges' desire for information about which applicants will enroll if admitted. Salazar et al. (2021) analyzed off-campus recruiting visits by 15 public research universities. Most universities made more out-of-state than in-state visits. These out-of-state visits focused on affluent, predominantly white public and private schools. Salazar (2022) analyzed visits to Los Angeles and Dallas by out-of-state public research universities. Analyses indicate that universities engage in "recruitment redlining – the circuitous avoidance of predominantly Black and Latinx communities along recruiting visit paths" [p. X]. Thus, contrary to branding by about the commitment to racial diversity (Holland & Ford, 2021), these studies find that the recruiting efforts of selective institutions prioritize affluent, predominantly white schools and communities.

A smaller set of studies analyze recruiting at open-access institutions that target working adults (e.g., Cottom, 2017; Posecznick, 2017). Cottom's (2017) analysis of the for-profit sector is simultaneously an ethnography of enrollment management and a work of political economy. For-profits found a niche in Black and Latinx communities precisely because traditional colleges ignored these communities. They systematically targeted women of color 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).

Because scholarship on recruiting assumes that recruiting is something done by individual colleges and universities, this literature ignores the role of third-party products and vendors. This blind spot has two causes. First, scholarship on recruiting has not considered the "platform studies" literature, which shows that digital platforms increasingly perform core organizational functions (e.g., Sadowski, 2019, 2020) and that digital platforms utilize algorithms that reinforce racial inequality (e.g., Benjamin, 2019). Second, scholarship on recruiting has not considred the broader enrollment management industry. Towards that end, Jaquette et al. (2022) provide a conceptual analysis of dynamics in the market for student list data. 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 by the product, the targeting behaviors 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. In turn, 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.

Salazar, Jaquette, & Han (2022) issued public records request to collect data about student lists purchased by public universities in four states. However, analyses sought to investigate 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, Figure 3 shows results from several "women in STEM" purchases, which filtered on some combination of SAT/AP score, GPA, state, and intended major. The racial and socioecnomic composition of purchased profiles differed dramatically from their surrounding metro area. Because of data limitations, Salazar et al. (2022) cannot determine which particular filters and filter thresholds are driving this exclusion. This paper advances beyond Salazar et al. (2022) in two ways. First, develop a conceptual framework that motivates propositions about structurally racist search filters that are likely to yield racial inequality. Second, we test propositions using a nationally representative sample of high school students, allowing us to examine who is included and excluded as filters and filter thresholds are changed.

4 Conceptual Framework

We develop a conceptual framework in two parts. First, we introduce concepts at the nexus of structural racism and algorithmic products, drawing largely from the sociology of race, but also from critical data studies and critical geography. Second, we apply these concepts to student list products and develop propositions about the relationship between search filters and exclusion.

4.1 Structural Racism and Algorithms

Structural racism. Contemporary sociology is largely concerned with a structural analysis of race. Bonilla-Silva (1997) argues that most social sciences define racism as an ideology held by individuals (e.g., explicit or implicit racial bias). This approach measures societal racism by examining the attitudes of individuals and excludes the possibility that institutions can be racist. Bonilla-Silva (1997) argues for a focus on the underlying social structure rather than the ideology associated with it. He defines "racialized social systems" as "societies that allocate differential economic, political, social, and even psychological rewards to groups along racial lines" (p. 474). Racial groups are a social construction of a racialized social system. For example, in the U.S. "black people" is a construct that emerges from the slave trade and its legacy. "Racial ideology" – commonly known as racism – is the ideological component of a racialized social system, which includes individual bias and also institutions that that benefit dominant racial groups. Bonilla-Silva (1997, p. 476) argues "that the only way to 'cure' society of racism is by eliminating its systemic roots." As the practices that produce racial inequality become increasingly covert, The sociology of race defines structural racism as a "a form of systematic racial bias embedded in the 'normal' functions of laws and social relations" (Tiako et al., 2021, p. 1143), whereby processes viewed as neutral or common-sense systematically advantage dominant groups and disadvantage marginalized groups.

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). Pioneered by the insurance industry, actuarial methods 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, individuals or businesses 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.[2] Hirschman & Bosk (2020) observes that actuarial methods can promote racial equity if the primary source of inequality is racial bias of individual decision-makers. For example, Korver-Glenn (2018) shows that homes in predominantly white neighborhoods received higher appraisal values than those in non-white neighborhoods because appraisers have discretion in selecting similar comparision homes ("comps") for the valuation. Scholarship from the sociology of race and critical data studies argues that actuarial methods reinforce structural racism through several mechanisms. We focus on two mechanisms: (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, p. 224) state that "predicting the future on the basis of the past threatens to reify and reproduce existing inequalities of treatment by institutions." 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

[2] Burrell & Fourcade (2021) observes that the adoption of actuarial methods across many industries was buoyed by concerns about racial equity following antidiscrimination legislation in the 1970s.

disadvantage non-white people and are correlated with race because non-white people have been historically excluded from this input (Harcourt, 2015; Hirschman & Bosk, 2020).

Obermeyer, Powers, Vogeli, & Mullainathan (2019) provide an empirical example of structurally racist inputs. They found that an algorithm used by hospital systems to predict patient health care needs under-predicted the needs of Black patients because the algorithm used health care costs as a proxy for health needs, but Black patients tend to receive less care relative to their health needs than other patients. An example by 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 it does include median household income, which is correlated with percent black because of historic wage discrimination. Once household income is included in the model, percent Black is not longer a significant predictor of city credit rating. Thus, household income is a "racialized input" Norris (2021), 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.

Geographic structurally racist inputs emerge from algorithms that make predictions based on where people live (Benjamin, 2019). Because targeting by race can be profitable, platforms often capitalize on residential segregation by using geography as an input to circumvent laws prohibiting race as an input. Thus, Benjamin (2019, p. 147) writes, "racialized zip codes are the output of Jim Crow policies and the input of New Jim Code practices."

The concepts "space" and "place" from critical geography (Agnew, 2011; Bell, 2007) provide insight about geographic structurally racist inputs. 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, p. 1), which develops geodemographic segment search filters, states 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." By contrast, scholarship on racial segregation conceives of geography as place. Racial segregation is a function of historic and contemporary structurally racist laws, policies, and practices promoting residential segregation (Harris, 1993; J. Howell & Korver-Glenn, 2018; Korver-Glenn, 2018; e.g., Rothstein, 2017). Algorithms that categorize people based on geographic location (space) without considering historic and contemporary structures (place) that produce residential segregation are to reproduce historical race-based inequality in opportunity.

Market segments and micro-targeting. A second source of structural racism in products utilizing actuarial methods 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 and target granular segments of society (Cotter, 2022).

In sociology, Fourcade & Healy (2013) define "classification situations" – which encompasses market segmentation – 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; customers are classified into many groups, or along a continuum, alongside the emergence of tiered products targeting different consumer groups with different benefit levels.For example, "payday loans" charge high interest rates to consumer groups that were previously denied credit altogether. Thus, at one end of the continuum, these classifications are similar to Cottom's (2017, 2020) concept "predatory inclusion," while 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 market segmentation (Benjamin, 2019; 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). Furthermore, classification systems are developed to optimize profit. In turn, "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" (Cotter et al., 2021, p. 3).

Critical data studies has also investigated micro-targeting (e.g., Benjamin, 2019; Cotter, 2022; Cotter et al., 2021). For example, Cotter et al. (2021, p. 1) state that micro-targeting by Facebook "is driven not by a goal of making all users available to advertisers, but of making the ‘right’ individuals available. Facebook advises that advertisers ‘Implement a targeting strategy that focuses on reach and precision and eliminates waste.’” 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. Instead, “campaigns routinely ‘redline’ the electorate, ignoring individuals they model as unlikely to vote, such as unegistered, uneducated, and poor voters (Kreiss, 2012, p. 74-75).[3]

4.2 Mechanisms of Exclusion in Student List Products

Conceptualizing student-list products. Student list products allow universities to choose prospective students from within some database of prospects by selecting on search filters. Salazar et al. (2022) categorize the filters available in the College Board Student Search Service product into the four buckets of geographic, academic, demographic, and student preferences (e.g., desired campus size, intended major), as shown in Table X.

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 products, student lists utilize search filters tha can be conceptualized as structurally racist inputs. For example, the College Board product 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 at the core of student list products. Universities are encouraged to execute multiple student list purchase, each targeting different market segments (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

[3] WE PULLED THIS QUOTE FROM COTTER 2021

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.). Recently, student list products have developed new search filters that utilize market segmentation and micro-targeting approaches that have been analyzed within critical data studies (Cotter et al., 2021; Noble, 2018). 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.[4] Other new filters are designed to increase precision, for example College Board's "interest in my peers" filter and ACT's predicted probability of enrollment filter. To the extent that universities want to target students from affluent schools and communities (Salazar et al., 2021), contemporary student list products facilitate this goal with great efficiency.

4.2.1 Predicting Exclusion

Our analyses focus 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. This section draws from the theoretical discussion above to develop propositions about the relationship between search filters and exclusion, focusing on academic and geographic search filters.

Academic filters. [KARINA + OZAN REVISE THIS SECTION AFTER SOME PRELIMINARY WORK] 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.

Broadly, the first source of racial and socioeconomic exclusion is that the underlying student list database excludes students who have not taken College Board assessments (SAT, AP, PSAT).[5] Prior research shows that test-taking rates differ by race and class. Thus, we expect that who is included in the underlying database exhibits racial and socioeconomic exclusion prior to conditioning on a particular assessment or a particular score.

A related source of exclusion within the population of test-takers is who takes which assessment. Students attending schools in affluent communities tend to have better access to AP curricula. Research shows that students from underrpresented populations are less likely to take the PSAT [CITE] or AP tests [TRUE? CITE?] [note that CB did not release AP partic-

[4] In 2021, College Board added three new geodemographic filters (College Board, 2021).
[5] footnote: recently added college search engine blah blah

ipation rates by race]. Therefore, conditioning on these assessments may increase exclusion. Additionally, College Board Search enables universities to target high school students early in the search process (e.g., sophomore PSAT takers) but students from underrepresented populations are more likely to take assessments later in high school (e.g., take SAT senior year). We expect that filtering for prospects early in high school is positively associated with racial and socioeconomic exclusion.

A second broad source of exclusion comes from test score thresholds utilized on filters. Test scores differ by race and class as a function of differential access to test preparation and . . . . [READ SOME STUFF AND THEN WRITE; STUFF FROM STRUCTURAL RACISM IN STANDARDIZED TESTING BY TIAKO AND RAY?]. We expect a positive relationship between test score thresholds and racial and socioeconomic exclusion. As an alternative to test scores, universities may filter on high school GPA or high school class rank [RESEARCH BY TIENDA AND FOLKS?]. We expect a weaker relationship between these filters and racial/socioeconomic exclusion.

Geographic filters. Geographic search filters enable universities to target prospects based on where they live. College Board Student Search Service offers two kinds of geographic search filters: filters based on known geographic borders (e.g., state, CBSA, zip code); and filters based on geographic borders that College Board constructs using historic data about test-takers (e.g, geomarket, geodemographic filters).

ONE OR TWO TRANSITION/SUMMARY SENTENCES REMINDING READER ABOUT GEOGRAPHIC STRUCTURALLY RACIST INPUTS

- Geographic search filters are built on the back of racial segregation. Targeting prospective students based on geographic location (space) without consideration to the historic and contemporary structures (place) that produce residential segregation is likely to reinforce historical race-based inequality in educational opportunity.

With respect to filters based on known geographic borders (e.g., county, zip code), we expect that utilizing finer geographic filters is associated with greater racial and socioeconomic dispairities in student list purchases because American residential segregation occurs at fine-grained geographic levels [CITE]. Prior research on recruiting, which finds that selective private and public research universities disproportionately target affluent schools and communities (Jaquette et al., forthcoming; Salazar, 2022; Salazar et al., 2021; Stevens, 2007), implies that some 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 of historical and contemporary practices that exclude people of color from living in many affluent neighborhoods.

In addition to filters for known geographic borders, College Board uses data on test-takers from previous admissions cycles to create new geographic borders for the purpose of filtering prospective students. “Geomarkets” divide metropolitan areas into smaller pieces. For example, the San Francisco Bay Area is divided into eight geomarkets, including CA10 the “City of San Jose” and CA11 “Santa Clara County excluding San Jose” [CITE]. Geodemographic segment filters utilize cluster analysis allocate each high school and each neighborhood (census tract) to a market segment based on based on past college-going behaviors of students from that school or neighborhood (College Board, 2011). The resulting classification is highly correlated with race because communities of color that have been historically excluded from higher education are more likely to be lumped together. More generally, we argue that filtering on geographic borders created from past education data is associated with racial exclusion because these borders likely reflect historic disparities in educational opportunity. Further, these filters increase the effects of historic place-based inequality because they enable universities to discriminate between prospects based on previously unknown geographic borders.[BUT CAN’T ANALYZE THESE CUZ WE DON’T HAVE/NEED TO CREATE THE BORDERS]

5 Discussion

What these platforms do with student data is opaque, because obfuscation is a deliberate strategy to avoid regulation (Cottom, 2020). Obfuscation is not an excuse for not doing the reasearch, but rather the reason that policy research must take on this challenge

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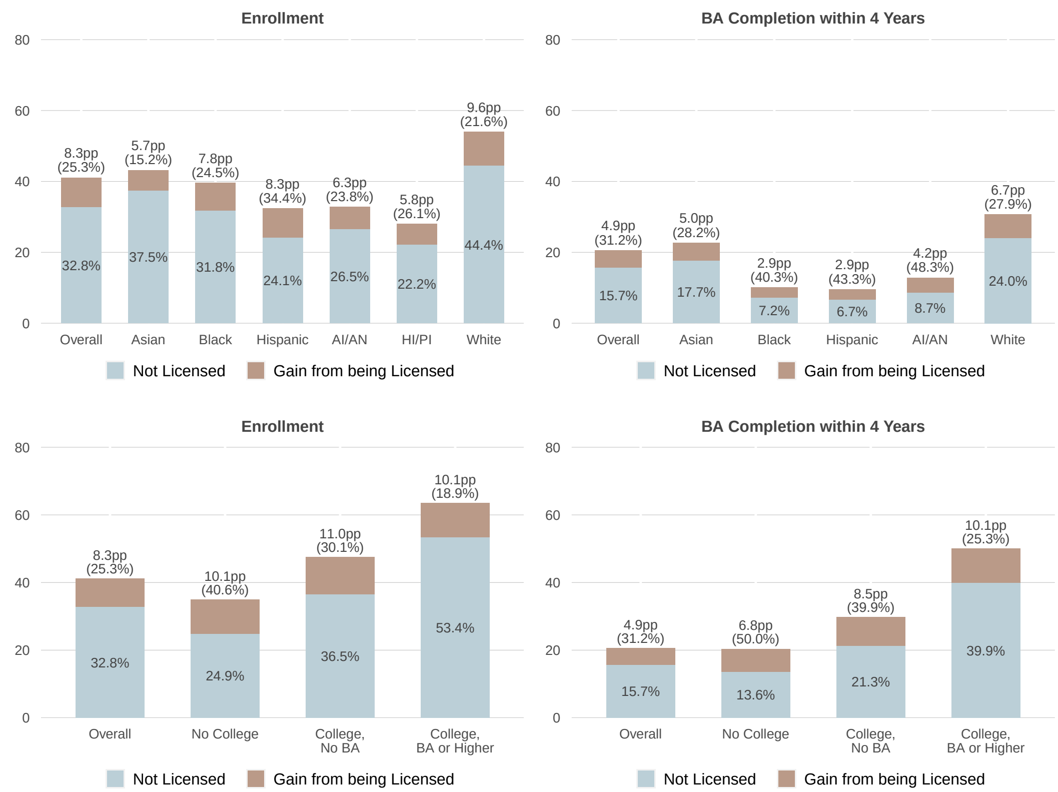
7 Figures

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: Women in STEM purchases compared to metro, average income and racial composition