Geodemographics of Student List Purchases by Public Universities: A First Look

Karina Salazar Ozan Jaquette Crystal Han

1 Introduction

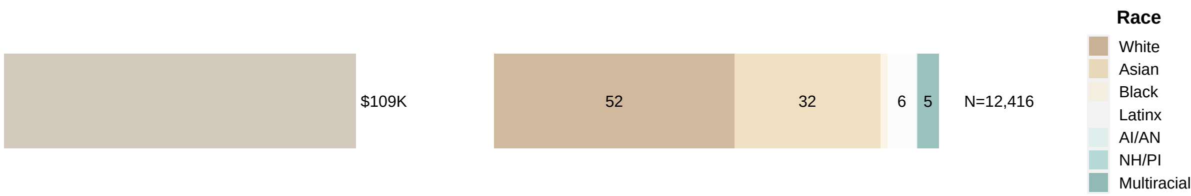
On March 8th 2020, a selective public research university purchased X [HOW MANY] "student lists" from The College Board. These lists contain demographic and contact information of prospective students that is collected when they complete assessments administered by the College Board. This information is purchased and then used by universities to recruit prospective students using mail, email, text messages, and other marketing interventions.

Several of the student lists purchased by the university targeted women in STEM fields. For example, an order the university named "NR 2021 Female AP STEM" targeted nonresident high school students from 26 states, who identified as women, were in the high school class of 2021, had an average high school GPA ranging from B to A+, and received a 4 or higher on an AP exam in a STEM subject (e.g., calculus, biology, chemistry, computer science, statistics). Another order titled "NR 2021 Female SAT STEM" utilized similar "search filters." However, the AP exam search filter was replaced by two filters: an SAT score between 1300 and 1600; and expressing interest in one or more STEM majors.

Research universities often purchase lists of female high school students – those who take STEM AP exams or those with SAT scores within some range who also express interest in a STEM major and – in order to overcome the under-representation of women in STEM degree programs. [1-2 SENTENCES ON POLICY CONCERN HERE?]. However, analyses of the prospects purchased by "women in STEM" orders suggests that efforts to solve inequities in one domain may lead to other problematic inequities.

Figure 1 shows the average racial and economic characteristics of the 12,938 prospects whose contact information was purchased across 11 total orders made by the university targeting women in STEM. These prospects live in zip codes where the average median household income is $109,000. Figure 1 also shows very few prospects whose information were purchased are Latinx (6%), Black (2%), Multiracial (5%), or Native American students (0.1%); whereas White (52%) and Asian (32%) students make up more than 8 of every 10 women in STEM prospects.

Figure 1: Women in STEM prospects, average income and racial composition



Efforts to increase representation of women in STEM by purchasing lists from College Board (or ACT) is likely to yield racial and socioeconomic inequality for two reasons. First, universities cannot purchase the contact information of prospects who are not included in the underlying database of test-takers. Exclusion from the database is a function of socioeconomic and racial disparities in access to AP coursework [CITE] and SAT/PSAT test-taking [CITE].[1].

Second, the "search filters" on student list products enable universities to control which prospects are included in a purchase. Although universities choose filters based on their preferences, these choices are structured by what the product allows. Several search filters (e.g., zip-code, AP exam score, "geodemographic" segment) may yield systematic racial, socioeconomic, and/or geographic inequality in which prospective students are recruiting by universities.

Prior research has not examined the search filter criteria universities select when purchasing student lists. Furthermore, research has not examined the characteristics of purchased prospects, or the relationship between filter criteria and student characteristics. Investigating these issues is important because recent research suggests that student lists have a surprisingly large effect on college access outcomes, particularly for students from populations that have been historically excluded from higher education (Howell, Hurwitz, Mabel, & Smith, 2021; Moore, 2017). We collected data about student list purchases by issuing public records requests to public universities in five states. This report focuses on student lists purchased from College Board and addresses three research questions:

1. Which filter criteria were selected in student lists purchased by universities in our sample?

[1]FOOTNOTE; ACT NRCCUA

2. What are the characteristics of prospects included in student lists purchased by universities in our sample?
3. What is the relationship between student list filter criteria and the characteristics of purchased prospects?

In the sections below, we provide relevant background about student lists, describe data collection and research design, present results for each research question, and discuss implications and future research.

2 Background

This section situates student lists within the admissions recruiting process. We describe how universities buy lists and what information they contain. We focus onlists sold by College Board, which are the focus of our empirical analyses. Last, we review recent research on the relationship between student lists and student outcomes

2.1 Situating Student Lists within Recruiting

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 "customers" (i.e., enrolled students). "Leads" are prospects whose contact information 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., by sending ACT scores). The funnel narrows at each successive stage – inquiries, applicants, admits – 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 [CITE].

At the top of the enrollment funnel, universities identify leads by buying student lists. Sometimes referred to as "names," student lists are the fundamental input for recruiting interventions that target individual prospects via mail, email, text, and on social media. The sum of purchased leads plus student-as-first-contact inquiries (e.g., filled out an online

Figure 2: The enrollment funnel

admissions inquiry form) constitutes the set of all prospects the university has contact information for, who are eligible to receive targeted recruiting interventions from the university.

2.2 Buying Student Lists

The largest student list vendors are College Board and ACT, which create student list products based on their database of test takers. College Board encourages students registering for PSAT, SAT, or AP exams to opt into the "Student Search Service," which enables "accredited colleges, universities, nonprofit scholarship programs, and nonprofit educational organizations" (College Board, 2022) to "license" their contact information. In fall 2021, College Board charged $0.50 per name (The College Board, 2021).

How do universities purchase student lists from College Board? Each purchased list is a subset of prospects drawn from the population of test-takers by specifying multiple search filters. Commonly specified search filters for student list names include high school graduation year, high school GPA, test score range (e.g., PSAT for purchases from College Board or PACT for purchases from ACT), gender, ethnicity, intended major, and geography (e.g., state, county, zip code) (Schmidt, 2019). As a hypothetical example, a university could purchase a student list from College Board that consisted of all prospects who scored between 1150 and 1520 on the PSAT, have a GPA higher than 3.5, live in one of the top 10 metropolitan areas, and are in the high school senior class of 2023. As we discuss below, College Board and ACT also offer filters that enable universities to target prospects based on the past college-going behavior of similar or nearby prospects.

What data do purchased student lists contain? Each purchased student list is essentially a spreadsheet that contains one row for each prospect that meets all criteria specified in the purchase. The columns of the student list include detailed contact information (name, address, email, cell phone) and detailed student characteristics derived from the pre-test questionnaire (e.g., high school graduation year, high school code, ethnicity, race, gender, intended major, first-generation status). The template for a College Board student list can be found here.

2.3 Student Lists and Student Outcomes

Recent research suggests that student lists substantially affect college access outcomes – and in turn degree completion outcomes – for millions of students each year. 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. Moore (2017) provides a similar analysis of ACT's Educational Opportunity Service (EOS). Figure 3 reproduces the main results of Howell, Hurwitz, Mabel, & Smith (2021). For students with the same values of SAT score, parental education, race/ethnicity, sex, high school 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, or a 25.3% change in the relative probability of attending a 4-year college.[2]

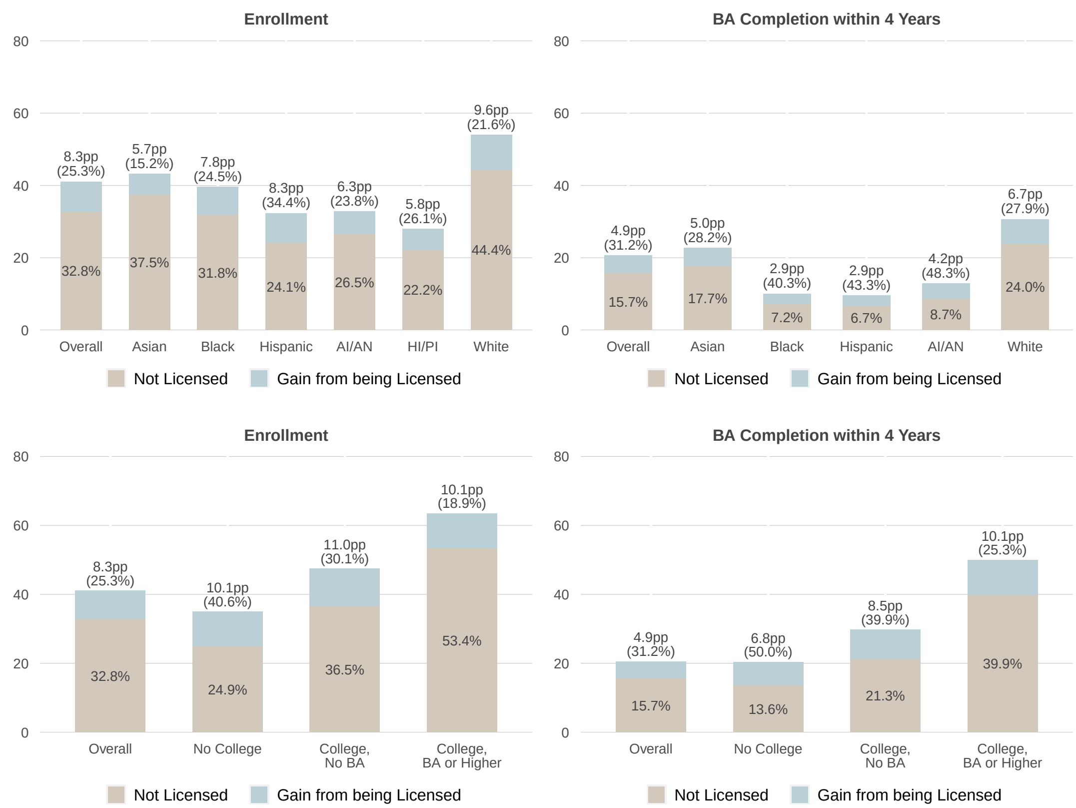
Figure 3 shows that participating in Search was associated with a larger percent change in the relative probability of attending a 4-year institution for students who identified as Black (24.5%), Latinx (34.4%), American Indian or Alaska Native (23.8%), and Native Hawaiian or Pacific Islander (26.1%) than it was for students who identified as White (21.6%) or Asian (15.2%). Similarly, the percent change in the relative probability of attending a four-year college was higher for students whose parents did not attend college (40.6%) than it was for students whose parents had a BA (18.9%).

Student lists may also affect degree completion through their effect on initial postsecondary

[2] Percentage point change = 41.1 - 32.8. Percentage change = (41.1-32.8)/32.8.

institution. Howell, Hurwitz, Mabel, & Smith (2021) analyzed the four-year BA degree completion rates of SAT test-takers from the 2015 and 2016 high school graduation cohorts. Figure 3 shows that 20.6% of students who participated in Search obtained a BA in four years compared to 15.7% of students who opted out, representing a 31.2% increase in the relative probability of graduation. Furthermore, the relative increase in the probability of obtaining a BA was higher for Black (40.3%), Hispanic (43.3%), and Native American/Alaska Native students (48.3%) than it was for White (27.9%) and Asian (28.2%) students. The relative increase in degree completion was also higher for students whose parents did not attend college (50.0%) than it was for students whose parents had a BA (25.3%).

Figure 3: Effects of College Board Student Search Service



Note: AI/AN = American Indian or Alaska Native. HI/PI = Hawaiian or Pacific Islander. The sample for enrollment outcomes includes all SAT takers in the 2015–2018 high school graduation cohorts. The sample for completion outcomes is restricted to students in the 2015–2016 cohorts. Completion results are not reported for HI/PI students due to very small sample size (N=2,749), which returns imprecise estimates. 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, and graduation cohort and high school fixed effects. All differences between students whose names were licensed and those whose names were not licensed are statistically significant at the 1% level.

3 Data Collection and Research Design

This section first describes the data collection for the broader student lists project from which this report draws from. Next, we describe the research methods for analyses of student list purchases from College Board, which are the focus of this report.

3.1 Data Collection

In 2019 we received funding from the Joyce Foundation and the Kresge Foundation for a project that would utilize public records requests via The Freedom of Information Act to collect data about recruiting practices, including student lists, from all public universities in four states, California, Illinois, Minnesota, and Texas.[3]

Public records requests. in February 2020, we began issuing public records requests to public universities. We issued one records request letter to each public university in our data collection sample (described below). An example records request letter can be found here. In subsequent communication we narrowed our request to student lists purchased from College Board, ACT, and the National Research Center for College and University Admissions (NRCCUA), the three largest student list vendors at the time.[4]

For each student list purchased for the purpose of undergraduate recruiting from 2016 through 2020, we requested two related pieces of data: (1) the order summary, which specifies search criteria for the student list purchase; and (2) the de-identified prospect-level list produced from the search criteria.

Figure 30 shows an example of a College Board order summary. In Figure 30, the university purchased the contact information of prospects who CRYSTAL ADD TEXT. With respect to de-identified prospect-level lists, this link shows partial data from the student list associated with this order. College Board student lists have one observation per prospect and contain variables for contact information (email and physical address), high school code, high school graduating class, demographic information, and selected information about college preferences (e.g., intended major).

Data collection sample. The data collection sample for the broader project consists of all public universities in IL, MN, CA, and TX. Additionally, we collected data from two

[3]We also requested data about off-campus recruiting visits

[4]NRCCUA PURCHASED BY ACT AND IN YEAR X ACT RELEASED ENCOURA PRODUCT THAT INTEGRATED NAMES COLLECTED FROM NRCCUA MYCOLLEGE OPTIONS PRODUCT

universities in a western state. Although the data we collected are public records, this report does not name individual universities in order to focus attention on student list products rather than the behavior of individual universities.

The IL higher education system includes 3 universities in the University of Illinois system, 7 in the Illinois State University system, and 2 in the Southern Illinois University system. In MN, there are 5 universities in the University of Minnesota system and 7 in the Minnesota State University system. In CA, there are 9 universities in the University of California system and 23 in the California State University system. In TX, there are 8 universities in the University of Texas system, 4 in the Texas State University system, 11 in the Texas A&M University system, 4 in the University of Houston system, 2 in the University of North Texas system, 2 in the Texas Tech University system, and 4 independent Texas universities.

Figures 4 and 5 describe the public universities in our data collection sample. A majority of the universities are master's or doctoral universities and located in urban areas.

Figure 4: University by carnegie classification

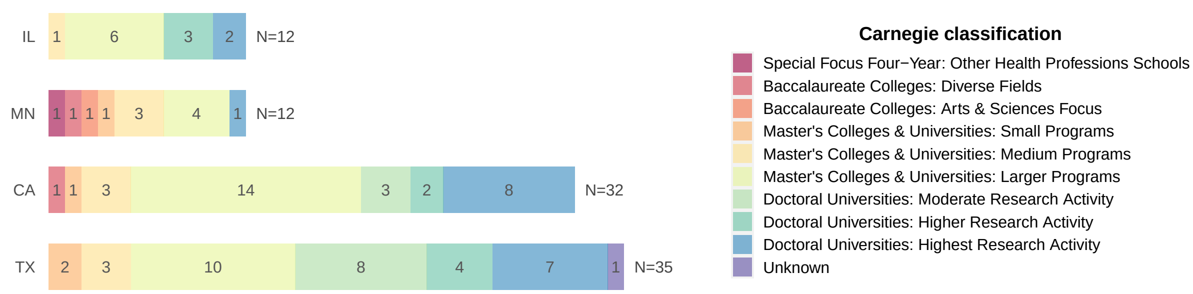
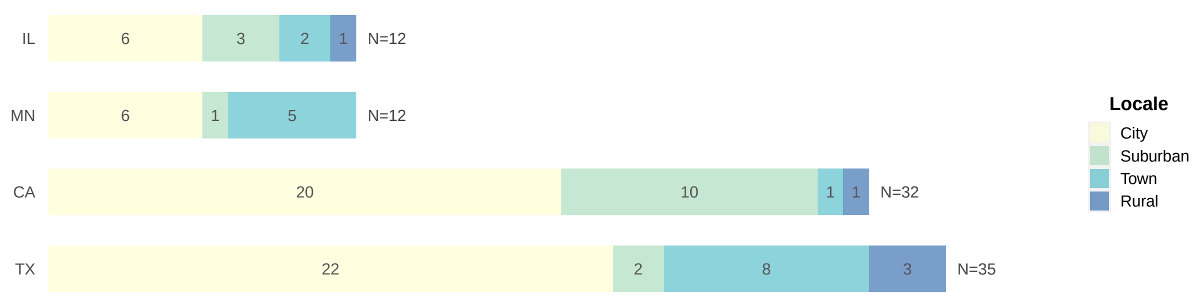


Figure 5: University by locale



Collecting quantitative data via public records requests is a painstaking process. Initially, most universities ignored or denied our requests. We later obtained pro bono representation from four law firms, although we were unable obtain representation for Texas. Firm representation substantially increased the success of data collection.

Nevertheless, data collection remained difficult. Some universities provided records that were not usable for quantitative analyses (e.g., obtained summary statistics across multiple orders, or data did not contain important fields). Some universities did not provide records based on legitimate grounds (e.g., data not in university possession; not required to create records that do not currently exist). Many universities outsourced student list purchases to a third-party consulting firm and we were rarely able to obtain usable data from these universities. Some universities denied requests based on questionable legal rationale, but we lacked the resources to pursue litigation.

Secondary data. Analyses incorporate several secondary data sources. Integrated Postsecondary Education Data System (IPEDS) data provides characteristics of universities in the analysis sample. NCES Common Core of Data (CCD) and Private School Universe Survey (PSS), respectively, provides data about U.S. public and private high schools. The Census American Community Survey (ACS) provide data about community characteristics. We use zip-code level data from ACS 5-year estimates. [CRYSTAL - ADD WHICH YEAR(S) OF DATA USED FOR EACH OF THESE SOURCES]

3.2 Research Design

Decisions about research design and research questions were constrained by the results of our data collection efforts.

Analysis sample. This report analyzes student lists purchased from College Board. We excluded purchases by MN public universities from the analysis sample because Minnesota is predominantly an "ACT state" and the majority of MN (regional) public universities primarily purchased lists form ACT rather than College Board.

Table 1 shows the number of public universities in our data collection sample that provided usable data about (1) student list order summaries and (2) de-identified student lists purchased from College Board. [CRYSTAL/KARINA - ARE THESE NUMBERS RIGHT?]. The results presented below are based on data received from 16 universities that provided usable order summary data and usable student list data.

Table 2 summarizes the number of order summaries received and the number of prospects purchased across the 16 [14?] universities.

- We received order summaries for 838 student list purchases, including XXXX purchases where we also received the associated prospect-level student list data and XXXX purchases where we did not receive the associated prospect-level list data.
- We received prospect-level student list data for 598 student list purchases, including XXXXX purchases where we also received the associated order summary and XXXXX

Table 1: Summary of data received

State	# received order summary	# no order summary	# received list	# no list	# received both	# did not receive both
IL	6	6	6	6	6	6
MN	6	6	6	6	6	6
CA	16	16	16	16	16	16
TX	18	17	18	17	18	17

Table 2: Summary of orders and prospects purchased

# orders total	# orders with list	# prospects total	# prospects with order
838	417	3,691,918	3,528,192

purchases where we did not receive the order summary. There were XXXX prospects in these 598 student list purchases, including XXXX prospects from purchases where we also received the associated order summary and XXXX prospects from the purchases where we did not receive the associated order summary. [CRYSTAL - FILL IN NUMBERS IN TEXT AND CHECK MATCH BETWEEN NUMBERS IN TEXT AND TABLES/FIGURES]

Appendix Figure 6 shows the number of student lists purchased by Carnegie Classification and state. Appendix Figure 7 shows the number of prospects purchased by Carnegie Classification and state. [CRYSTAL - MOVE THESE FIGURES TO APPENDIX]

Figure 6: Summary of orders purchased by carnegie classification

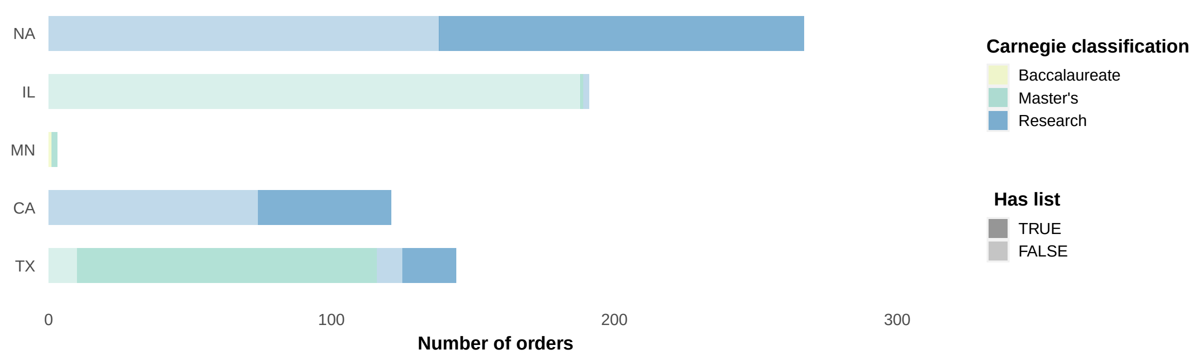
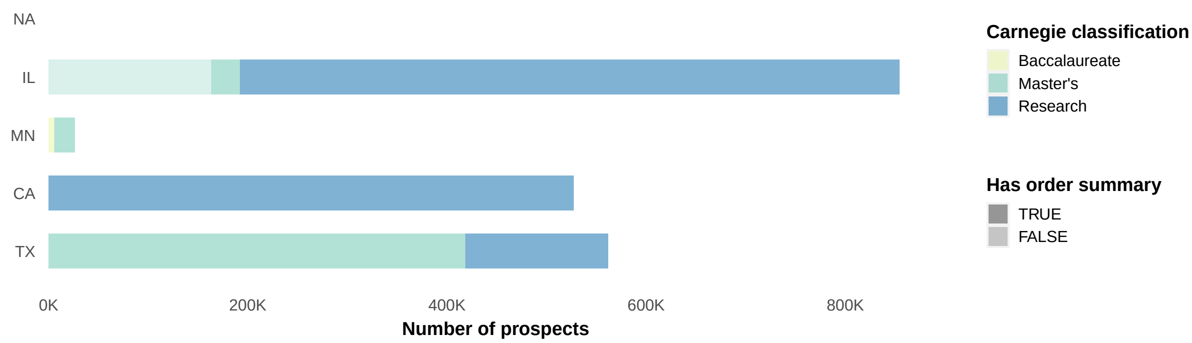


Figure 8 presents the 838 total orders – purchased by 16 universities – by university type and total students purchased. The six master's universities in the purchased 307 lists, while research universities made 530 orders.

The number of total prospects purchased within each order varied widely. Across all 838 orders, the median number of prospects purchased per order was 1,016, whereas the mean was 5,638 (sd=17,696). Despite making fewer total orders than master's universities, research universities on average purchased nearly double the number of students per order (7,542

Figure 7: Summary of prospects purchased by carnegie classification



versus 2,382). Results are strongly influenced by universities that made a large number of orders (RQ1) and purchased a large number of prospects (RQ2). In particular, one public research university made XXX orders and purchased XXX prospects [CRYSTAL - ADD NUMBERS FOR ASU].

Figure 8: Orders and prospects purchased by research vs. ma/doctoral

Research questions. Choices about research questions were informed by data limitations and by substantive considerations. Because we received order summary data and student list data from a non-random sample of universities, we utilize a multiple case study research design (Eisenhardt, 1989) rather than a large-N statistical design. Therefore, our analysis sample identifies behaviors that exist in the population of public universities, but not the prevalence of these behaviors in the population.

More substantively, analyses should also focus on student list products themselves, not just the behavior of customers (universities) who buy the product. Systematic inequality in purchased versus excluded names is a function of: (A) which prospective students are included in the underlying data base; (B) the set of filters that universities can utilize to select prospects; and finally (C) university choices about which filters to select. Therefore, analyses investigate the relationship between the filters chosen for a particular student list purchase and the characteristics of prospects included in the resulting student list.

The empirical analyses presented in this report are guided by three research questions, which focus on student lists purchased from College Board:

1. Which filter criteria were selected in student lists purchased by universities in our sample?
2. What are the characteristics of prospects included in student lists purchased by universities in our sample?
3. What is the relationship between student list filter criteria and the characteristics of purchased prospects?

In RQ1 the unit of analysis is the order or university-order. Analyses allow us to make statements about how orders vary – within-university variation and between-university variation – for universities in our sample. In RQ2 the unit of analysis is university-prospect. Analyses allow us to make statements about the characteristics of prospects targeted by universities in our sample. In RQ3 the unit of analysis is order-prospect. Analyses allow us to make statements about the relationship between filter criteria and prospect characteristics that extend to lists purchased by any university that select similar filter criteria.

Analyses. Empirical analyses consist of simple descriptive statistics presented in tables, figures, and maps. For each research question, analyses are anchored by a small set of tables or figures that present results for the entire analysis sample. Next, we present analyses of selected universities, purchases and/or localities that convey commonly observed or thematically important patterns, with a focus on the nexus between race, class, and geography. For RQ2 and RQ3, we contextualize the characteristics of purchased prospects by showing the characteristics of one or more comparison groups (e.g., all high school graduates in the metropolitan area).

4 Results

4.1 RQ1: Filter Criteria Selected in Purchases

Our first research question asks which filter criteria were selected in student lists purchased by universities in our sample. We first describe broad patterns in filters used by research vs. ma/doctoral universities. The filters commonly used by universities in our sample can be categorized into three groups: academic (e.g., GPA, PSAT, SAT, academic rank, AP Score); geographic (e.g., zip code, state, segment, core based statistical area, geomarket, international); and demographic (e.g., race/ethnicity, gender). A fourth group of filters were also used to capture student preferences (e.g., campus size, campus location, major interests, etc), although these were used less frequently than academic, geographic, and demographic filters. Next, we describe patterns observed, for academic, geographic, and demographic filters, respectively, and how filters are used in combination.

4.1.1 Broad Patterns

Figure 9 shows how often filters were used by university type. While student list purchases typically filter on multiple criteria, Figure 9 illustrates the prevalence of each individual filters.

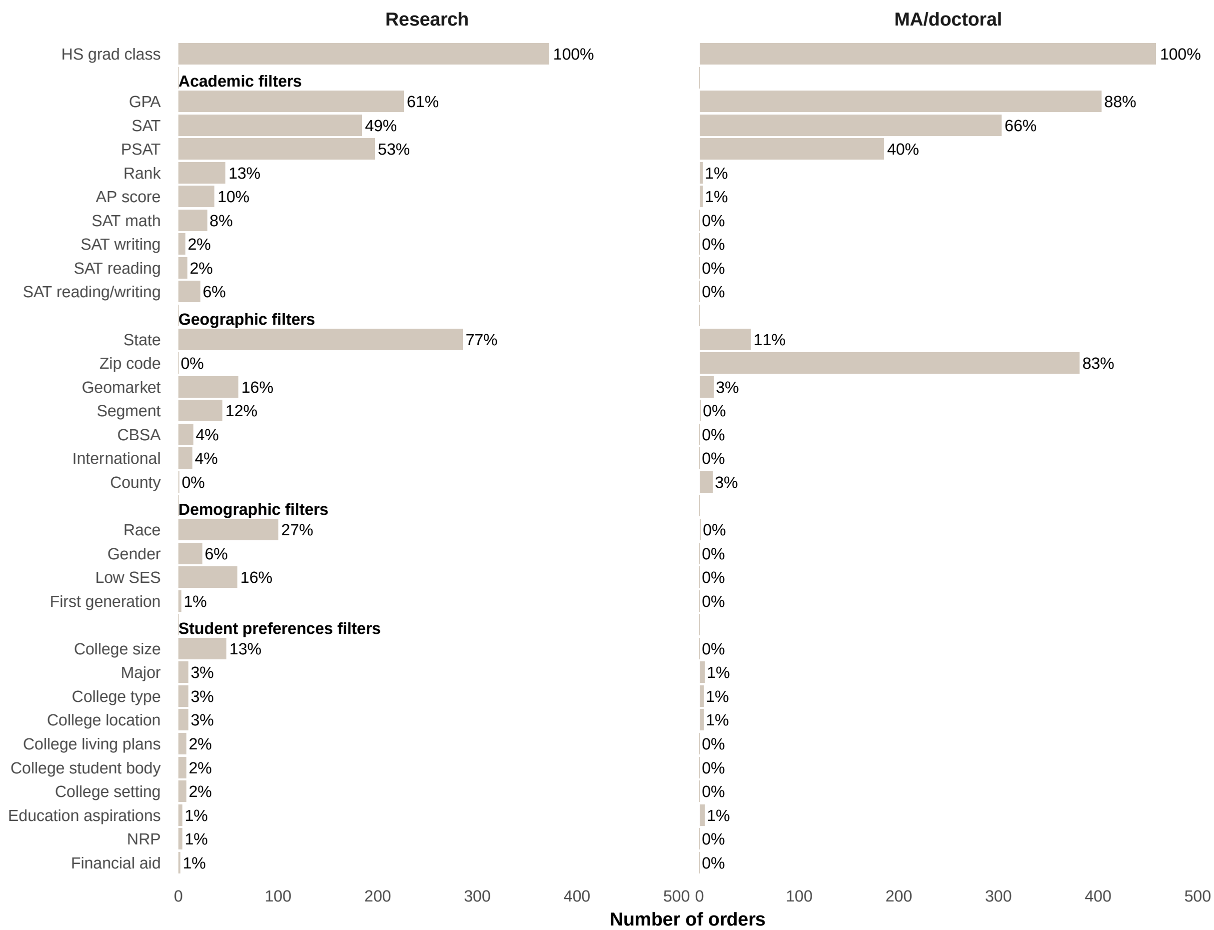
All orders by both research universities (n = 377) and ma/doctoral universities (n = 458) filtered by high school graduation class. Commonly used academic filters across university type include GPA, SAT, and PSAT. Compared to ma/doctoral universities, research universities were somewhat less likely to filter on GPA or SAT score and more likely to filter on PSAT score. Additionally, research universities filtered on high school class rank (13% of orders) and AP score (10% of orders), but few ma/doctoral orders utilized these filters.

Orders by ma/doctoral versus research universities differed across geographic filters. About 77% of orders by research universities used a state filter but only 11% of orders by ma/doctoral universities filtered for entire states. More than 8 of every 10 orders by ma/doctoral universities used a zip-code filter. However, it is worth noting that most of these orders came from one doctoral university that recruits out-of-state students extensively. By contrast, research universities in our sample did not use zip code filters. However, research universities also filtered by geomarket (16%), segment (12%), core based statistical area (4%), and international status (4%), whereas ma/doctoral universities generally did not but did use county filters (3%).

MA/doctoral universities did not utilize demographic filters. For research universities, about 27% or orders filtered by prospects' race/ethnicity. About 16% of orders by research universities also filtered for prospects that we're categorized as low-income, although the majority of these orders came from one research university. Orders by research universities also filtered prospect by gender (6%), first-generation college student status (1%), and financial-aid need (1%).

Lastly, filters for student preferences were used primarily by research universities, although as frequently as academic, geographic, and demographic filters. For ma/doctoral universities, prospects' preferences for major, college type, college location, and educational aspirations were used, individually, across 1% of orders. On the other hand, about 13% of orders by research universities filtered for prospects' preferences for college size. Other prospect preferences used as filters across orders by research universities include major (3%), college type (4%), college location (3%), college setting (2%), college living plans (2%), recognition of programs (1%), and educational aspirations (1%).

Figure 9: Filters used in order purchases by research vs. ma/doctoral

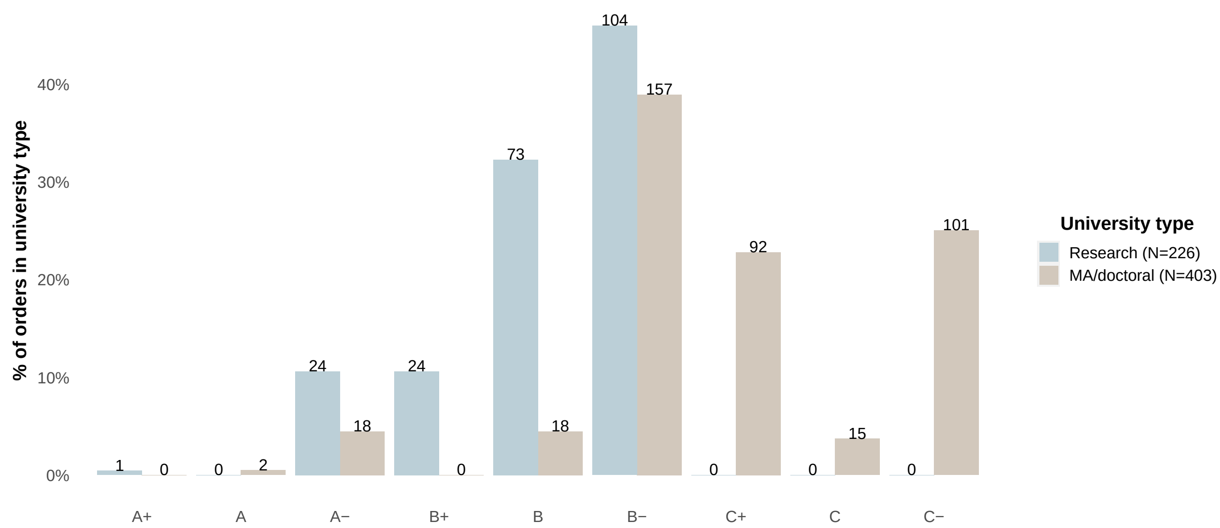


4.1.2 Academic Filters

The three most commonly used academic filters (GPA, PSAT, SAT) were used by specifying a "low/minimum" and a "high/maximum" threshold. Across university type, nearly all orders that filtered on GPA used a high threshold of "A+."[5] However, Figure 10 shows that research and ma/doctoral universities differed in the specified low threshold for orders filtering by GPA. For research universities, low GPA thresholds ranged from A+ to B-, with the majority of orders using a low of B- (46%) or B (33%). However, ma/doctoral universities' orders used low GPA thresholds that ranged from A to C-, with more than half of these orders specifying a low between C- and C+.

Figure 11 shows minimum and maximum thresholds used in SAT score filters and 12 shows thresholds for PSAT. Although substantial overlap exists across university type, research universities tended to specify higher minimum score thresholds and higher maximum score thresholds across both SAT and PSAT compared to ma/doctoral universities. In Figure 11, for example, 21% of orders by research universities specified a minimum SAT score of 1100 or lower compared to nearly 60% of orders by ma/doctoral. For maximum thresholds, nearly 75% of orders by research universities specified an SAT score of 1310 or higher compared to 42% of orders by ma/doctoral. Interestingly, 7% of ma/doctoral universities' SAT filter orders indicated a minimum SAT score threshold of 1500+, whereas research universities made zero orders at that minimum threshold. These 21 orders were made by two different ma/doctoral universities targeting prospects for specific scholarship programs.

Figure 10: GPA filter used by research vs. ma/doctoral



4.1.3 Geographic filters

The research universities in our sample used different geographic filters than the ma/doctoral universities in our sample. About 77% of orders by research universities filtered on state

[5]The only exception is one order by a research university that used a GPA high of A-

Figure 11: SAT filter used by research vs. ma/doctoral

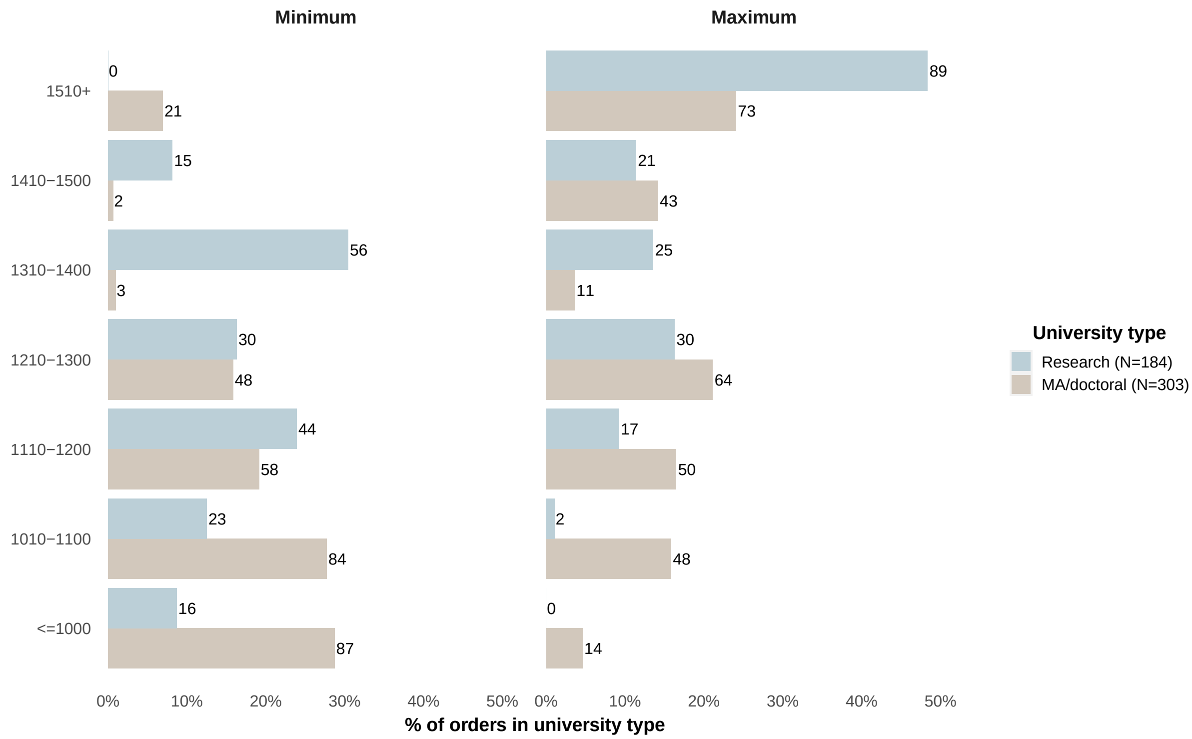
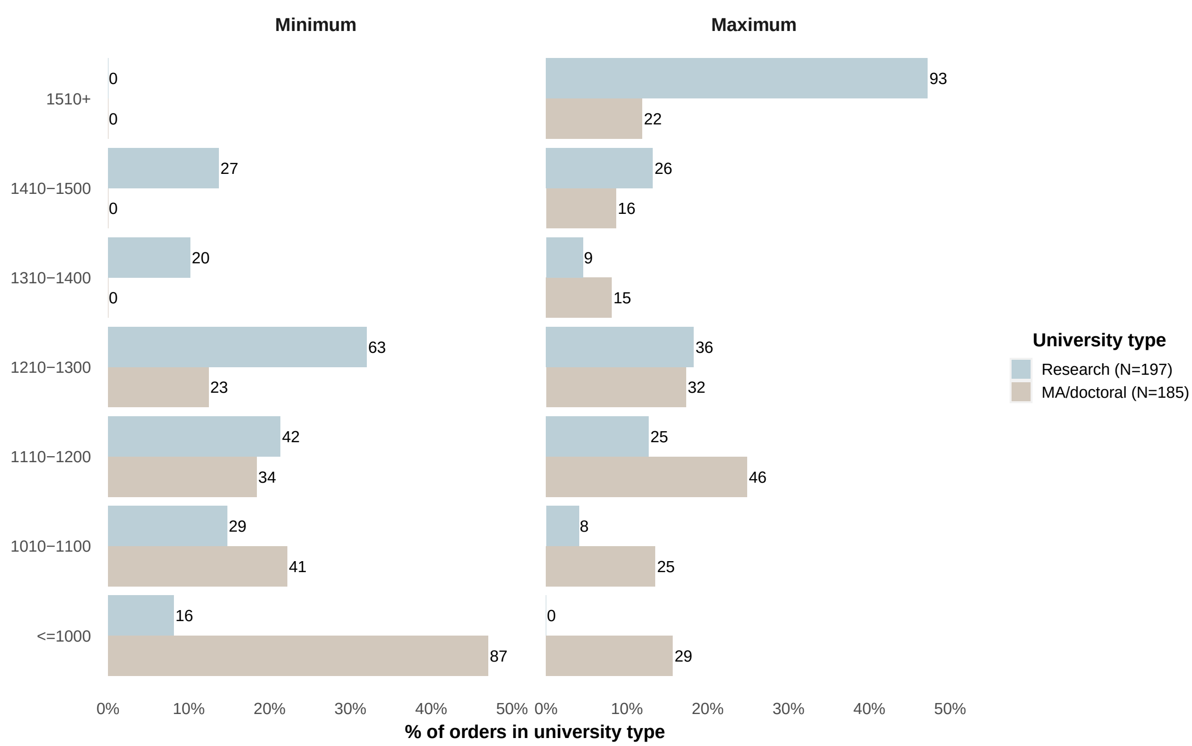


Figure 12: PSAT filter used by research vs. ma/doctoral



(Figure 9). These orders filtered on multiple states or on a single state. Orders that filtered on multiple states were used to target out-of-state prospects. The majority of single-state orders were used to target in-state prospects. However, single-state orders to target out-of-state prospects in populous states (e.g., CA) were also common.

Figures 14 and 15 show orders by research universities that filtered on state for orders that filtered on out-of-state prospects and in-state prospects, respectively. California, Texas, Arizona, and Illinois were the most commonly filtered states by universities searching for out-of-state prospects (see14. Orders for out-of-state prospects tended to avoid less populous and less affluent states.

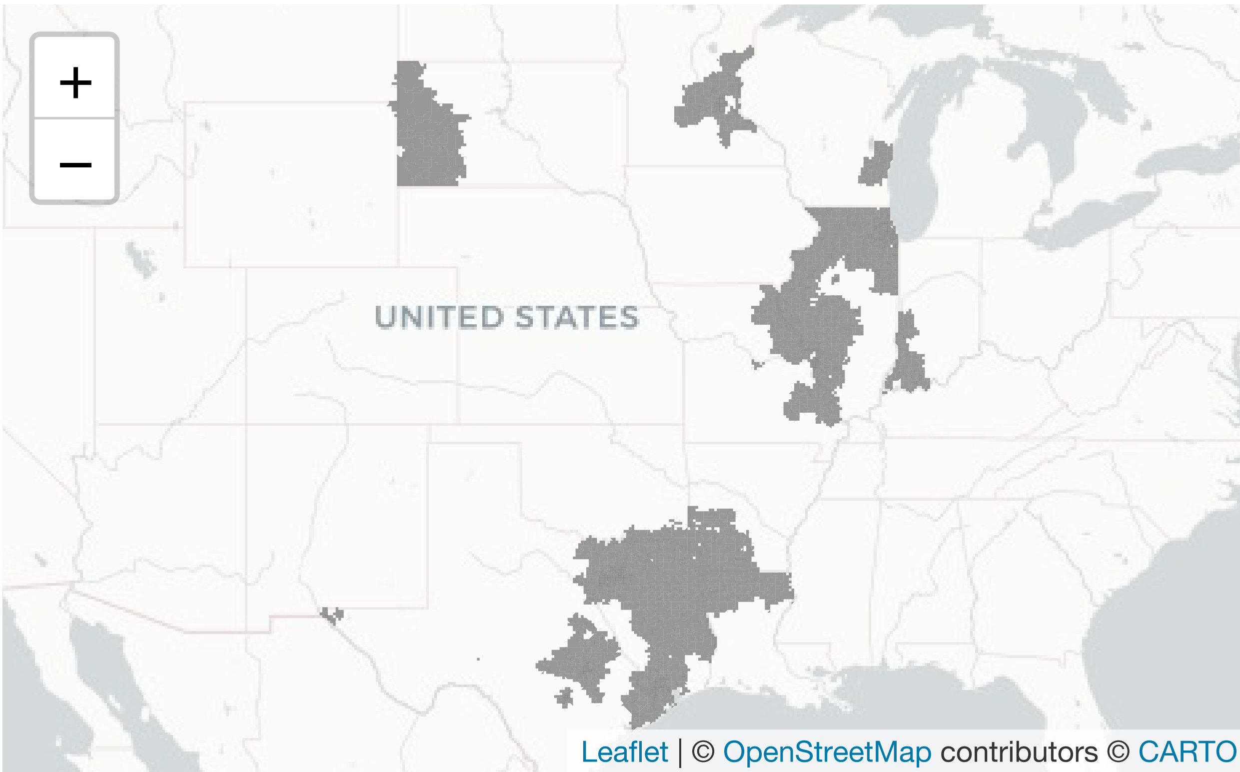
Aside from state, research universities also filtered on other geographic filters created by College Board, including "geomarkets" (16% of orders), "segment" (12% of orders), CBSA (4%), and 4% of order targeted international prospects. Geomarket filters are created by the College Board within their Enrollment Management Services, which use information about SAT score senders from the past five admissions cycles within a specific geographic locality (e.g., counties, metropolitan areas, cities) to make projections about high school graduates in the area [CITE].

Segment filters come from the College Board's "Segment Analysis Service," which categorizes each high school and each neighborhood (census tract) into a type based on its demographic, geographic, academic, historical college-going characteristics (The College Board, 2011). Universities can then filter on prospects who attend a particular "type" of high school and/or live in a particular "type" of neighborhood. We analyze Segment orders in more detail in Research Question 3, below.

The geographic filters most commonly used by ma/doctoral universities in our sample were state, home zip code, and county. 11% of orders by ma/doctoral universities filtered on state. These orders primarily were used to target in-state prospects or prospects in regional, neighboring states. About 83% of orders by ma/doctoral universities filtered on home zip code, but orders by research universities did not filter by zip code.

Zip code filters were used by ma/doctoral universities in two different ways. In the first approach, universities filtered for three-digit zip codes. Three digit zip codes are prefixes for all five-digit zip codes that fall within a postal service sectional center facility, many of which serve large metropolitan areas within one state but can sometimes serve multiple states. About 224 of 381 orders that filtered on zip code filtered on three-digit zip codes. Orders using three-digit zip codes tended to target areas within the state where the university resides and sometimes in neighboring states, which is likely a function of ma/doctoral universities targeting prospective students in their local regions. Figure 13 shows a map of three-digit zip codes filtered by a public university located in Texas.

Figure 13: 3-digit zip code filter used



In the second approach, universities specified specific zip codes to use as filters in a separate spreadsheet or text file that was provided to College Board. Unfortunately, our research team was unsuccessful in acquiring these separate files after many attempts. However, because orders that did include specific zip code filters (by printing them on the order summary rather than in separate file) were all the three-digit level, we presume that orders using external files for zip code filters were at the five-digit level. Therefore, we estimate that about 41% (n=157) of the 381 orders using zip codes filtered on five-digit zip code.

For example, one doctoral university gave us order summaries for 136 student lists they purchased from College Board from April 2019 through February 2020. About 64% of these orders (n=87) specified using a text file to filter for zip code, presumably at the five-digit level. While we were unable to obtain these zip code text files, the names on these orders (e.g., 'Midwest/South II 950-1040 Srs (20),' 'West II Srs (20) AP 3-5') suggests that most of these orders targeted out-of-state five-digit zip codes.

Filtering by geography always raises concerns for prospects who do not reside in the targeted geography. Filtering by five-digit zip code is particularly concerning because there is no equality of opportunity rationale for targeting students who live in one zip code but not those from a neighboring zip code. Zip codes are highly correlated with income and racial demographics. Therefore, policymakers may be concerned that some universities are systematically excluding low-income communities or communities of color when they filter on five-digit zip code.

Figure 14: State filter used by research universities, out-of-state

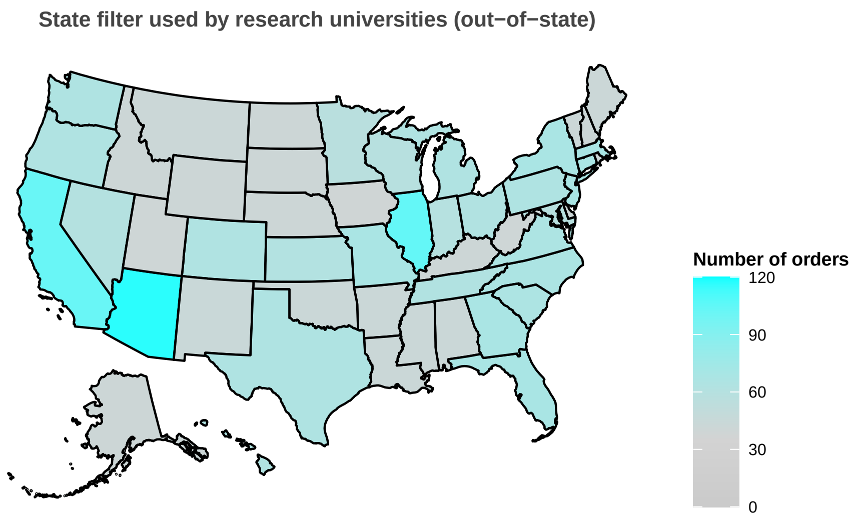
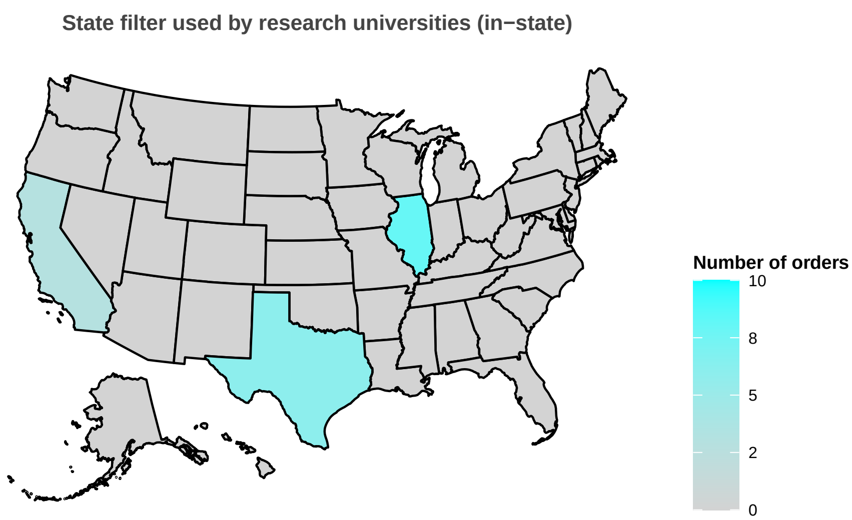


Figure 15: State filter used by research universities, in-state

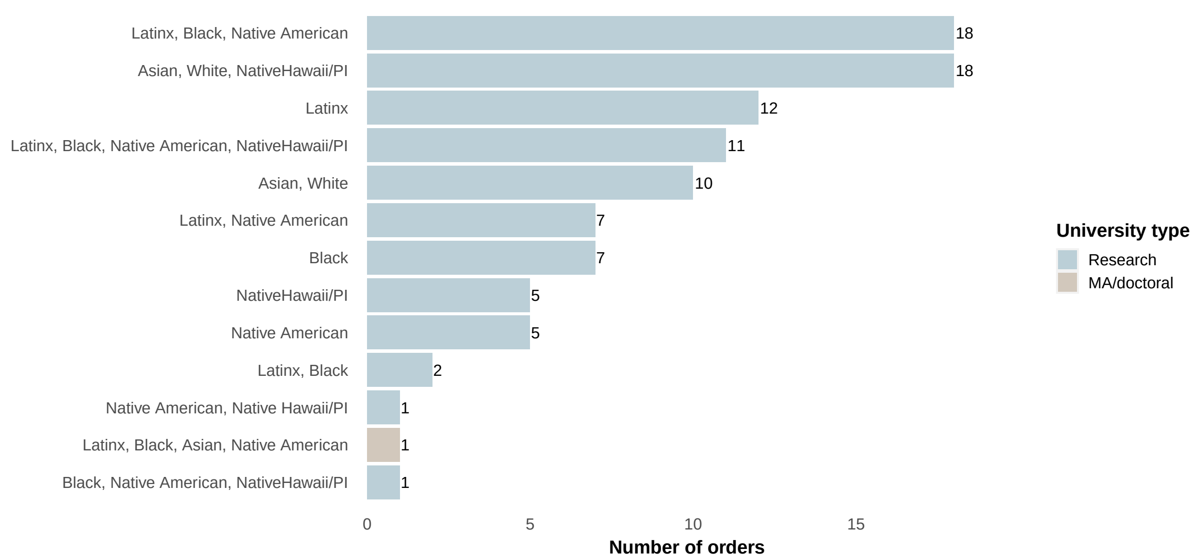


4.1.4 Demographic Filters

Nearly all orders using demographic filters were made by research universities. Figure 15 shows the number of orders that used a race/ethnicity filter. Most of the 103 orders using race/ethnicity filters specified multiple race/ethnicity groups. This includes 19 orders that filtered by Black, Native American, or Latinx prospects and 19 orders that filtered for Asian, Native Hawaiian/Pacific Islander, and White prospects. Other common race/ethnicity filter combinations include Latinx, Black, Native American, and Native Hawaiian/Pacific Islander (11 orders); Asian and White (10 orders); and Latinx and Native American (7 orders). Fewer orders filtered for only one race/ethnicity group, including 12 orders filtering for Latinx prospects, 7 orders filtering for Black prospects, 5 orders for Native Hawaiian/Pacific Islander, and 5 orders filtering for Native American prospects (American Indian/Alaska Native).

About 59 orders by public research universities filtered prospects by low-income status, with 58 of these orders made by one research universities. The low-income status filter defined low-income prospects as those with family incomes less than $45,000. Research universities also made 24 orders using gender filters. Across these orders, 75% filtered for women prospects and 25% filtered men prospects. Other demographic filters used include first-generation college student status (3 orders filtered for prospects with parents with no or some college) and financial-aid need (2 orders filtered for prospects with no response, not planning on applying, or undecided about financial aid).

Figure 16: Race filter used by research vs. ma/doctoral



4.1.5 Combination of Filters

On average, orders by research universities (N=377) specified five filter criteria, whereas orders by ma/doctoral universities (N=458) specified four filter criteria. Table 3 shows the ten most commonly used combinations of filters across orders by university type. However, it is important to note that filter combinations are skewed by universities that made large numbers of orders relative to other universities (see Figure 8). [OJ: STATE SOMEWHERE THAT SOME FILTER IN THESE COMBINATIONS AREUSED AS **OR** CONDITIONS RATHER THAN **AND** CONDITIONS? KS: Did they actually specify "or" rather than "and?" and how many orders did this?].

For research universities, the top ten filter combinations account for 51% of all orders. The most common filter combination, making up 10% of all orders, included high school graduation class, state, race, SAT, PSAT, GPA, and high school rank (n=39). For 29 orders, the second most common combination only used high school graduation class, state, and PSAT score filters, which were also used for the remaining top five combinations in addition to filters like race, gpa, low-socioeconomic status, and students' preference for nationally recognized programs. The 6th most common combination also used high school graduation class, state, and GPA filters but switched PSAT to SAT scores. The remaining common filter combinations across orders by research universities used other academic filters (e.g., high school rank, AP scores) and geographical filters (e.g., geomarkets, segment).

For ma/doctoral universities, the top 10 filter combinations account for 95% of all orders. This is a function of nearly half of all orders using a combination of high school graduation class, zip, SAT scores, and GPA to filter prospect lists. Another 32% of orders used these same filters but used PSAT scores rather than SAT scores. Other orders by ma/doctoral universities used similar patterns of filters by using all three top academic filters together (PSAT, SAT, and GPA) or switching zip codes for a state filter.

The results for Research Question 3 below investigates the student characteristics associated with particular combinations of filters.

Table 3: Filter combos used in order purchases by research vs. ma/doctoral

Research			MA/doctoral		
Filters	**Count**	**Percent**	**Filters**	**Count**	**Percent**
HS grad class, GPA, SAT, PSAT, Rank, State, Race	39	10%	HS grad class, GPA, SAT, Zip code	206	45%
HS grad class, PSAT, State	27	7%	HS grad class, GPA, PSAT, Zip code	145	32%
HS grad class, GPA, PSAT, State, Race	20	5%	HS grad class, SAT, State	31	7%
HS grad class, PSAT, State, Low SES	20	5%	HS grad class, GPA, SAT, PSAT, Zip code	28	6%
HS grad class, GPA, PSAT, State	17	5%	HS grad class, GPA, SAT, State	7	2%
HS grad class, GPA, SAT, State	16	4%	HS grad class, SAT, Geomarket	6	1%
HS grad class, GPA, AP score, Geomarket	15	4%	HS grad class, GPA, SAT, County	5	1%
HS grad class, GPA, SAT, PSAT, State, Segment, Gender	13	3%	HS grad class, GPA, SAT, PSAT, County	4	1%
HS grad class, PSAT, Geomarket	12	3%	HS grad class, GPA, PSAT, State	2	0%
HS grad class, SAT, State, Low SES, College size	11	3%	HS grad class, SAT, Geomarket, College type	2	0%

4.2 RQ2: Characteristics of Prospects

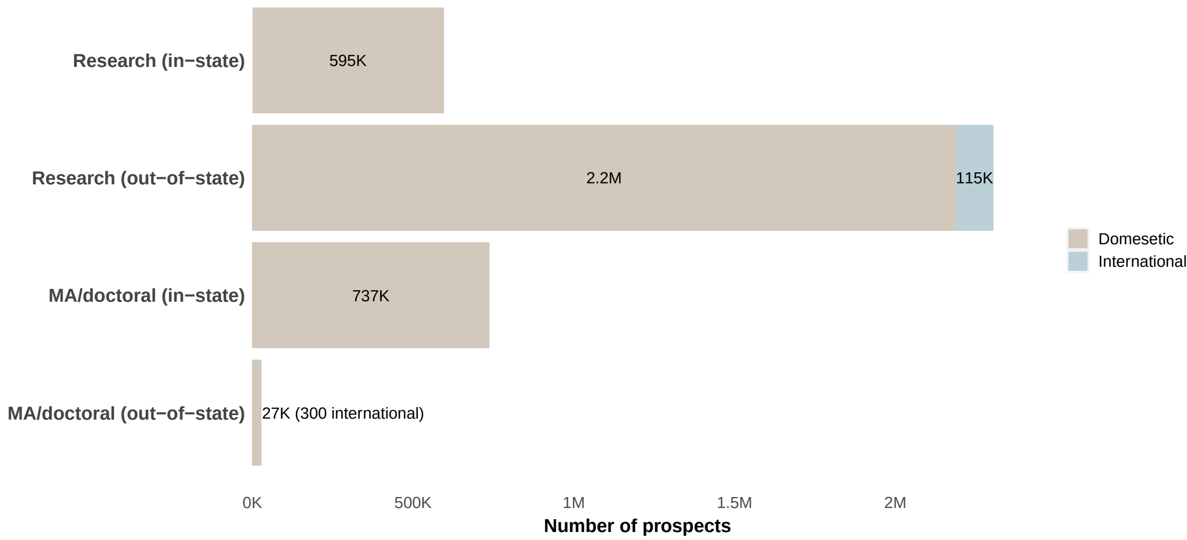
Research Question 2 asks, What are the characteristics of prospects included in student lists purchased by universities in our sample? Our analysis on the characteristics of prospects purchased by universities includes 598 orders resulting in 3,691,918 prospects. Figure 17 shows the total number of prospects by public versus ma/doctoral universities, focusing on domestic students. Research universities in the study purchased nearly four times the number of prospects (N= 2,785,481) than ma/doctoral universities (N=764,334).

Figure 17 shows the number of prospects purchased by in-state versus out-of-state across institutional type. Research universities purchased many more out-of-state students than ma/doctoral universities. For example, of the nearly 2.8 Million prospects purchased by research universities, 79% were out-of-state. For ma/doctoral universities, only 5% of the nearly 791,000 prospects were out-of-state students.

Below we describe the racial, economic, and geographical characteristics of prospect lists purchased by research and ma/doctoral universities.

Reporting ethnicity and race. College Board's voluntary demographic questionnaire asks students separate questions about ethnicity (Cuban, Mexican, Puerto Rican, other Hispanic, non-Hispanic, ethnicity non-response) and about race (American Indian or Alaska Native, Asian, Black, Native Hawaiian or other Pacific Islander, White, race non-response). For both ethnicity and for race, the questionnaire allows students to check as many boxes as they want, including "I do not wish to respond" and "other" [CITE]. From these responses, we created the College Board "derived aggregate race/ethnicity" variable, which is based on U.S. Department of Education reporting guidelines and includes the following categories: no response; American Indian/Alaska Native; Asian; Black; Hispanic/Latino; Native Hawaiian or Other Pacific Islander; White; other; two or more races, non-Hispanic [CITE]. Any student who selects a Hispanic ethnicity category is defined as Hispanic/Latino, regardless of the race categories they select, which reduces the number of students defined as belonging to a particular race group (e.g., Black, American Indian/Alaska Native). Additionally, note that non-Hispanic students who check "American Indian or Alaska Native" and another race group are defined as "two or more races, non-Hispanic." We detail the percentage of prospects that did not report their race/ethnicity, with missing race/ethnicity, and those reporting other race/ethnicity in the figures for research question 2 below. However, given the relatively small proportion of prospects within these categories, they are dropped from figures thereafter for ease of interpretation.

Figure 17: Number of prospects purchased by university type and location



4.2.1 Public Research Universities

Figure 18 presents the racial characteristics of prospects from lists purchased by research university across in-state versus out-of-state status. Out-of-state prospects in lists purchased by research universities had a larger proportion of White and Asian students and lower proportions of Black, Latinx, and Native American students than lists for in-state prospects. Across all research universities, out-of-state prospects were 50% white students, 19% Asian students, 17% Latinx students, 4% Black, 6% multiracial, and 4% no response. By contrast, in-state prospects were 38% white students, 11% Asian, 26% Latinx, 5% Black, 4% multiracial, and 14% of students that did not report their race/ethnicity.

Figure 19 presents the average median income of the zip code where in-state versus out-of-state prospects live, indicating that out-of-state prospects tend to be more affluent than in-state prospects. Across all research universities, out-of-state prospects lived in zip-codes where the average median household income was $98,000. In-state prospects lived in zip-codes where the average median household income was $85,000.

Figure 20 examines the extent to which in-state and out-of-state prospects purchased by research universities tend to reside in urban, suburban, or rural zip codes, as defined by the NCES/Census "locale" variable [CITE]. 34% of in-state prospects lived in urban areas and 39% lived in suburban areas. By comparison, out-of-state prospects were less likely to live in urban areas (25%) and more likely to live in suburbs (47%). The percentage of prospects living in rural areas was about the same for in-state and out-of-state prospects. The majority of rural prospects purchased lived in "rural-fringe" areas (less than 5 miles from an Urbanized

Figure 18: Racial composition of prospects purchased by research universities

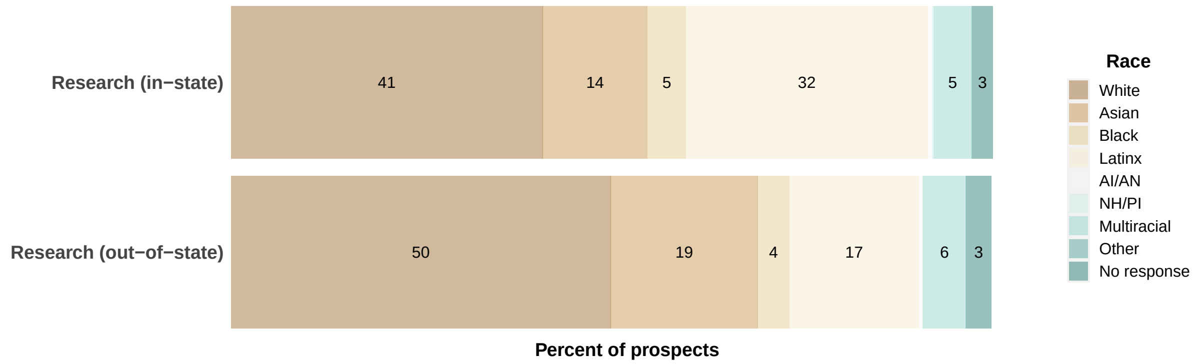
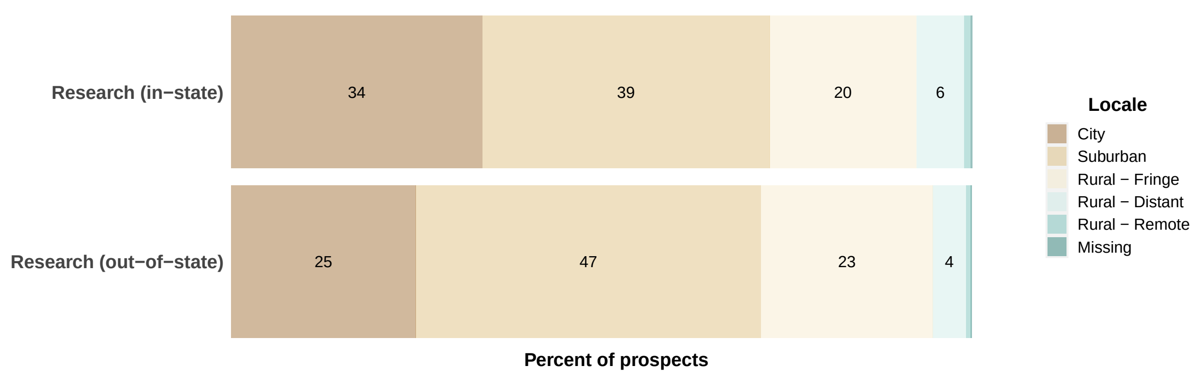


Figure 19: Median household income of prospects purchased by research universities

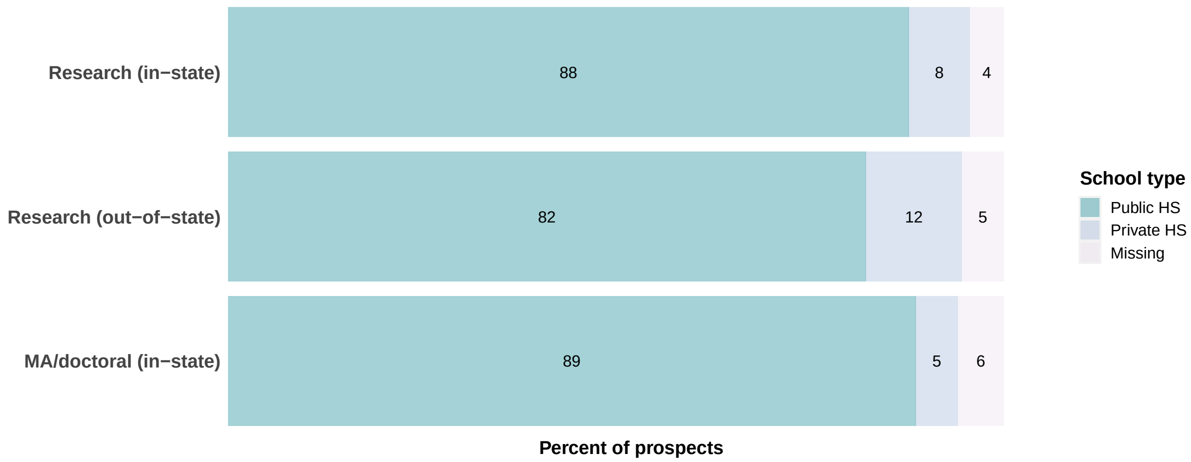
Figure 20: Locale of prospects purchased by research universities



Area or less than 2.5 from an Urban Cluster) rather than "rural-distant" or "rural-remote." Future research should analyze name buys in rural areas more thoroughly.

Finally Appendix 21, shows that the percentage of out-of-state prospects attending private high schools (12%) was higher than the percentage of in-state prospects attending private schools (8%).

Figure 21: School type of prospects purchased by research vs. ma/doctoral universities



4.2.2 Public ma/doctoral Universities

Analyses of prospects purchased by ma/doctoral universities focus on in-state prospects because the ma/doctoral universities in our sample purchased few out-of-state prospects, except for one university which provided us data about order summaries but not the associated prospect-level data.

Figure 22 compares the racial characteristics of in-state prospects purchased by ma/doctoral universities to the racial characteristics of in-state prospects purchased by research universities. Greater proportions of in-state prospects for ma/doctoral universities identify as White and Black, whereas greater proportions of in-state prospects for research universities identify as Asian, Latinx, and multiracial. For example, ma/doctoral universities' in-state prospects are 46% White, 10% Asian, 8% Black, 26% Latinx, 1% American Indian/Alaska Native, 0.1% Native Hawaiian/Pacific Islander, 4% multiracial, and 5% did not report their race/ethnicity. Whereas research universities' in-state prospects are 41% White, 14% Asian, 5% Black, 32% Latinx, 1% American Indian/Alaska Native, 0.2% Native Hawaiian/Pacific Islander, 5% multiracial, and 3% did not report their race/ethnicity

Figure 23 compares the household income of in-state prospects purchased by ma/doctoral universities to that of in-state prospects purchased by research universities. For ma/doctoral universities, in-state prospects lived in zip codes where the average of median household income was $94,000. By contrast, the in-state prospects purchased by research universities were slightly more affluent, living in zip codes where the average of median household income was $99,000.

Figure 22: Racial composition of prospects purchased by ma/doctoral universities

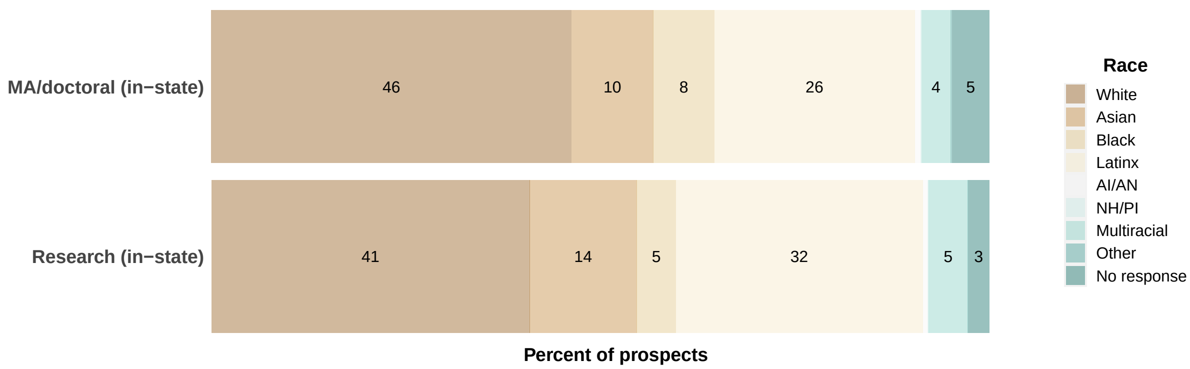


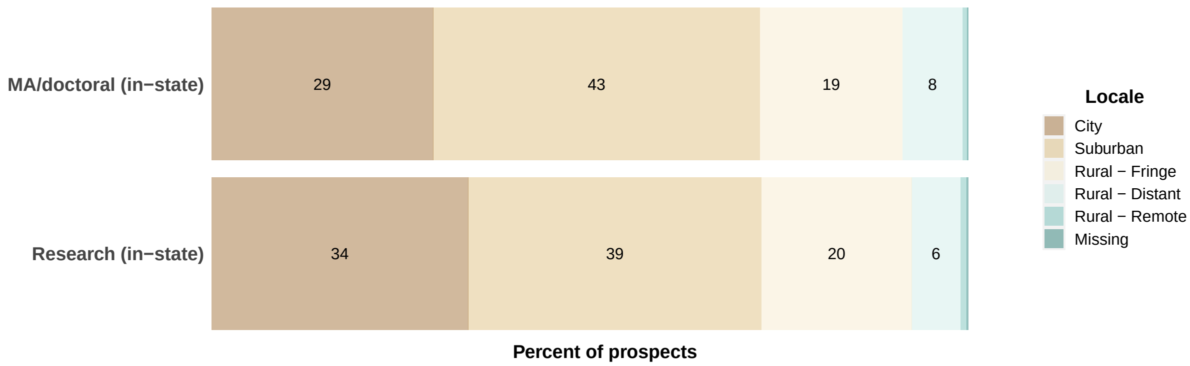
Figure 23: Median household income of prospects purchased by ma/doctoral universities

Figure 24 examines the locale (city, suburban, rural) of in-state prospects. Compared to research universities, ma/doctoral universities purchased a slightly higher percentage of prospects living in suburban areas (43% compared to 39%) and a slightly lower percentage of prospects living in cities (29% compared to 34%). The share of prospects residing in rural areas was nearly identical across university type.

4.3 Filter Criteria and Characteristics of Prospects

We analyze the relationship between filter criteria and the characteristics of purchased prospects in two different ways. First, we analyze prospect characteristics (e.g., race/ethnicity, income, in-state versus out-of-state) across individual filters to understand broad patterns.

Figure 24: Locale of prospects purchased by ma/doctoral universities



Second, we analyze prospect characteristics across common combinations of filters. Here we use selected universities, purchases and/or localities that convey commonly observed or thematically important patterns across combinations of filters. We also contextualize the characteristics of purchased prospects by showing the characteristics of one or more comparison groups based on the selected examples.

4.3.1 Prospect Characteristics Across Individual Filters

Table 4 presents the characteristics of prospects by individual filters. For each column, averages are reported across all prospects that were purchased via orders using the specified column filter, which includes orders that used the specified filter in combination with other filters.[6]

Focusing on the racial characteristics of prospects, student lists with the largest percentages of White and Asian prospects result when orders use PSAT, gender, segment, or CBSA filters. For example, orders that specify a gender filter result in prospect lists that are less than 10% Black, Latinx, and/or Native American. This pattern is consistent in prospect lists that use segment or CBSA filters, although the disparity is not as large for orders using a PSAT filter (24% Black, Latinx, Native America). On the other hand, orders that filter by specifying particular race/ethnicity groups result in lists that have fewer White and Asian prospects and greater proportions of Black, Latinx, Native American, and multiracial prospects. This coincides with descriptive findings above that suggest more than half of all orders using a race/ethnicity filter specified Black, Native American, and/or Latinx prospects.

Similar disparities are evident across the economic characteristics of prospect lists by filters

[6] Given we present all prospects across individual filters that are used in combination with others, total number of prospects summed across columns will exceed our grand total of 3,691,918 prospects

Table 4: Prospect characteristics by filter used

		Academic					Geographic					Demographic	
	All domestic	GPA	PSAT	SAT	HS rank	AP score	Zip code	State	Geomarket	Segment	CBSA	Race	Gender
Total count	3,547,620	1,101,266	1,812,447	971,237	146,660	75,479	165,924	1,173,678	1,056,951	186,519	146,313	279,626	39,546
Location													
% In-state	38	62	30	54	83	42	98	48	17	15	4	59	6
% Out-of-state	62	38	70	46	17	58	2	52	83	85	96	41	94
Race/ethnicity													
% White	48	45	50	47	51	17	43	42	57	51	53	25	47
% Asian	16	15	17	15	10	7	13	18	13	27	28	5	38
% Black	5	7	4	7	8	17	8	5	4	3	2	11	1
% Latinx	21	24	19	22	23	46	27	24	16	11	8	46	6
% NH/PI	0	0	0	0	0	1	0	0	0	0	0	0	0
% AI/AN	1	1	1	0	1	1	1	1	0	0	0	2	0
% Multiracial	5	5	5	5	5	10	4	6	5	5	5	9	5
% Other	0	0	0	0	0	0	0	0	0	0	0	0	0
% No response	4	3	3	3	2	1	4	3	4	3	3	2	3
% Missing	0	0	1	0	0	0	1	1	1	0	0	0	0
Gender													
% Male	34	19	37	18	0	3	46	24	48	6	0	11	0
% Female	36	23	40	20	1	15	54	27	52	9	0	12	33
% Other	0	0	0	0	0	0	0	0	0	0	0	0	0
% Missing	30	58	22	63	99	82	0	49	0	85	1	77	67
Household income													
Median income	$107K	$105K	$108K	$105K	$99K	$90K	$97K	$105K	$107K	$130K	$135K	$94K	$127K
Locale													
% City	27	27	27	26	26	31	31	30	23	24	22	29	26
% Suburban	44	47	44	48	53	40	42	42	46	54	57	47	49
% Rural - Fringe	22	20	22	20	15	23	19	22	23	19	19	19	23
% Rural - Distant	6	6	5	6	6	5	7	6	6	2	1	6	2
% Rural - Remote	1	0	1	0	0	0	1	1	1	0	0	0	0
% Missing	0	0	0	0	0	0	0	0	0	0	0	0	0

used. Orders using PSAT, gender, segment, or CBSA filters result in prospect lists with the largest average median household incomes. Orders using a CBSA filter showcase the upper extreme of this pattern, resulting in lists where the average prospect lived in a zipcode where the median household income $117,000. Similarly, orders using race/ethnicity filters showcased the lower extreme. When universities purchased orders that filtered for specific race/ethnicity groups, the resulting lists included prospects that lived in zip codes where the average median household income was less than $85,000.

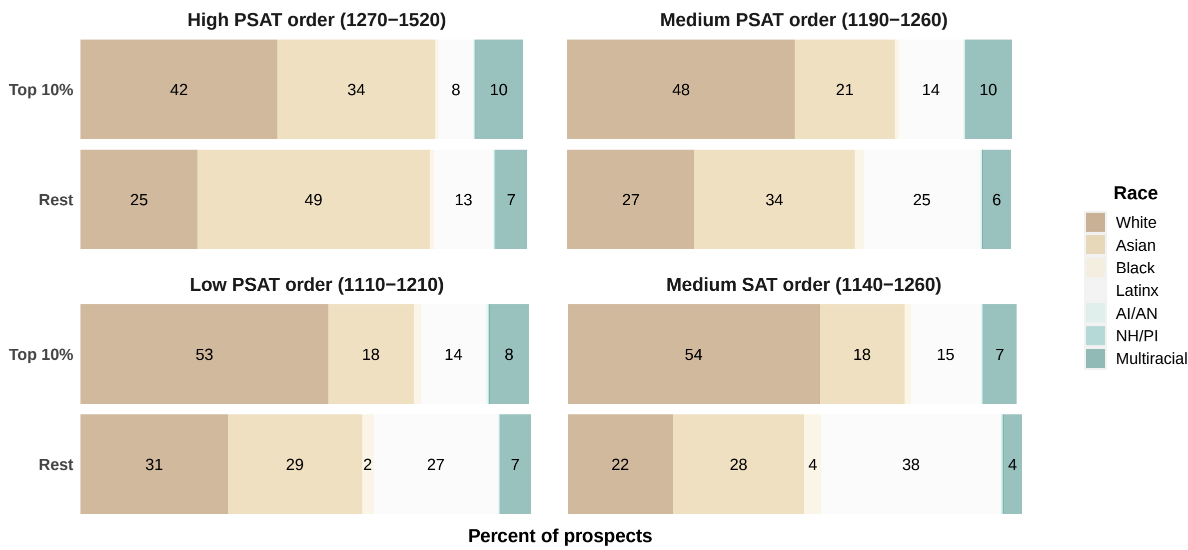
Not surprisingly, orders using geographic filters result in specific patterns of in-state versus out-of-state prospects. However, analyzing the residency status of prospect lists across filters can help us develop insights into how specific filters are used to target prospects geographically. For example, orders using segment and CBSA filters are likely used for targeting out-of-state students, as the use of these filters result in prospect lists made up of 85% and 96% out-of-state prospects, respectively. However, orders filtering for prospects within specific state(s) result in list that are nearly equal proportions of out-of-state and in-state students. Coinciding with descriptive statistics detailed above and data limitations (i.e., we only received zip codes used to filter order lists by two master's universities in our sample), nearly 98% of prospects resulting from orders using a zip code filter were in-state students. Similar to disparities in racial and economic characteristics of prospects, orders using a gender filter also resulted in geographical disparities (94% out-of-state versus 6% in-state).

Lastly, Table 4 shows the difference in proportions of prospects that attend public versus private schools does not change significantly across filters used. For example, orders that specify a CBSA result in student lists where on average 14% of prospects attend private schools, which is the maximum proportion across all filters. In comparison, orders that use zip code filter result in students lists with the minimum proportion of prospects attending private schools (7%).

4.3.2 Prospect Characteristics Across Combinations of Filters

4.3.3 Zip Code & Test Score Filters

Figure 25: Zip code deep dive



One common combination of filters used across orders were zip codes and test score ranges. Zip code filters were used primarily by indicating a list of five-digit zip codes, usually stored as a text or excel file provided to the College Board, from which orders then filtered prospects by. While we were able to obtain order summaries from several universities that indicated filtering by five-digit zip code, we were unsuccessful in acquiring the student list data and the additional files listing five-digit zip code filters for these orders after many attempts. In the process of requesting the additional data and files, some universities using zip code filters revealed that they were not in possession of the files. Rather, universities stated that student list purchases were made through a third-party enrollment management consulting firm on their behalf and that the firm possessed the files.

While we are unable to analyze the specific zip codes used to filter prospects for the orders in our study, we conduct an analysis using a hypothetical zip code filter to investigate whether and to what extent filtering prospects by five digit zip codes reveals racial disparities. To do this, we draw on one university's student list purchases within one metropolitan area. These prospects were filtered by a combination of SAT and PSAT filters and an out-of-state filter for the entire state, thereby casting a larger net than if the university would have additionally filtered by five digit zip codes. Using the resulting list of prospects in the metropolitan area, we apply a hypothetical five-digit zip code filter and categorize prospects into two comparison groups. The first group, prospects that live within any of the specified zip codes, are those that would still be included in purchased students lists if the university applied an additional zip code filter. The second group, prospects that do not live within any of the specified zip codes, are those that would be excluded from purchased student lists by the additional zip code filter. By comparing the two groups across racial characteristics, we are able to replicate which prospects the university included in purchased student lists via the state filter but would have missed through the use of additional zip code filters.

We draw on student lists purchased by one research university for this analysis. Besides filtering for prospects in their home state, California was the only other single-state filter used across all orders by the university. The university made a total of 37 orders targeting California high school students graduating in 2019-2022, with 20 of these orders only using PSAT or SAT filters in addition to the state and high school graduating class. Because the university purchased the largest number of California prospects from the Los Angeles metropolitan area (N=114,604) across all orders, we "zoom" into and apply the hypothetical zip code filter to the resulting Los Angeles prospect lists for four individual orders representing low, medium, and high PSAT and SAT score ranges used.

We draw on research that speaks to general recruiting trends for public research universities to select a hypothetical zip code filter for the analysis. For example, Jaquette and Curs (2015) found that public research universities dramatically increased nonresident enrollment from 2002 to 2012 in response to declines in state appropriations because nonresident tuition prices are often more than double the price of resident tuition. Our research on off-campus recruiting events finds that public research universities tend to visit affluent (and predominantly white) out-of-state high schools, likely in efforts to recruit nonresident students that can contribute to the revenue goals of the institution (Salazar, onlinefirst; Salazar, Jaquette, & Han, 2021). Therefore, we leverage a hypothetical zip code strategy that attempts to replicate these efforts in student list purchases.

Student lists purchased by the university include at least one prospect from 355 of the 378 total zip codes in the Los Angeles metropolitan area. We use the top 10% of these 378 zip codes (n=38) by median household income as a zip code filter. These top 10% zip codes range from \$120,000 to \$210,000 in median household income and encompass areas like Bel Air, Newport Coast, Beverly Hills, and Malibu. The other zip codes falling in the bottom 90% range from \$22,000 to \$118,000 in median household income and encompass areas like East L.A., Whittier, and Pasadena.

Figure X presents the racial characteristics of Los Angeles prospects across four different orders using the hypothetical zip code filter. Given the greatest number of Los Angeles prospects were selected by orders using PSAT filters, the figure presents results for three orders using PSAT scores and one order using SAT scores. For example, the "high" PSAT order filtered for California prospects with PSAT scores ranging from 1270 to 1520, resulting in a student list of 6,658 prospects from the Los Angeles metropolitan area. When we apply the hypothetical zip code filter, 1,384 of the 6,658 prospects live in one of the top 10% zip codes and are included in the purchased student list. On the other hand, 5,274 of the 6,658 prospects do not live in one of the top 10% zip codes and make up the group of prospects that would be excluded from the purchased student list if we apply the hypothetical zip code filter

The figure illustrates disparities in the percent of Asian, Latinx, and Black "high PSAT" prospects that would be "included" or "excluded" from the student list by the hypothetical zip code filter. For instance, if the university would have applied the zip code filter, "high PSAT" prospects included in the purchased student list would be, on average, 42% White, 34% Asian, 10% Multiracial, 8% Latinx, 0.7% Black, and 0.1% Native American. However, prospects excluded by the zip code filter and not in the student list purchased by the university would be 25% White, 49% Asian, 7% Multiracial, and 13% Latinx. A greater proportion of Black (1%) and Native American (0.2%) would also have been missed using a zip code filter, although the magnitude in the difference to those included is relatively smaller.

The disparities between the racial characteristics of prospects included or excluded in purchased student lists become more pronounced across orders using lower test score ranges. The "medium" PSAT order filtering for PSAT scores from 1190-1260 resulted in a student list of 6,826 prospects, the 1,049 of those prospects included in the student list after applying the zip code filter are 48% White, 21% Asian, 14% Latinx, 10% Multiracial, 1% Black, and 0.3% Native American. Similar to the high PSAT order, a larger proportion of Asian (34%) and Latinx (25%) prospects are represented in the 5,777 of the 6,826 prospects that would have been excluded from the purchased list if the zip code filter was used.

These patterns are most pronounced in the largest student list order (N=14,875) resulting from filtering for "low" PSAT scores ranging from 1110 to 1210. The 2,194 prospects still included in the student lists after applying the zip code filter are, on average, 53% White, 18% Asian, 14% Latinx, 8% Multiracial, 1% Black. However, the 12,681 prospects excluded by the zip code filter and not purchased by the university are, on average, 31% White, 29% Asian, 27% Latinx, and 2% Black.

Figure X also shows the racial characteristics of prospects included and excluded from student lists by the hypothetical zip code filter for an order using SAT scores. While a relatively smaller number of prospects from the Los Angeles metropolitan area were selected from orders using SAT filters, they also ranged across "low," "medium," and "high" score ranges. Figure X illustrates an order using a "medium" range for scores from 1140 to 1260, which resulted in a student list of 4,081 prospects. Similar to orders using lower PSAT score ranges, the combination of the hypothetical zip code and "medium" SAT score filter results in large racial disparities. Prospects that would be included in the student list (N=481) after applying the zip code filter are, on average, 54% White, 18% Asian, 15% Latinx, 7% Multiracial, 2% Black, and 0.4% Native American. However, Latinx (38%), Asian (28%), and Black (4%) prospects make up much larger proportions of students that would be excluded from the purchased student list if using the zip code filter (N=3,594).

4.3.4 Geodemographic Segment Filters

College Board began offering geodemographic search filters with the creation of the Segment Analysis Service (herein Segment). Geodemography – now often referred to as "spatial big data" – is a branch of market research that estimates the behavior of consumers based on where they live. According to The College Board (2011):

> 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. When they are living in a community, people. . . share similar patterns of consumer behavior toward products, services, media, and promotions. The primary appeal of geodemography from the marketer's perspective is that, with just an address, s/he can begin to craft an image about a particular set of individuals based on the values, tastes, expectations, and behaviors associated with their geographic community (p. 1).

This quote illustrates that geodemography is based on problematic assumptions. People with similar cultural backgrounds do not "naturally gravitate toward one another" (The College Board, 2011, p. 1). Rather, U.S. neighborhoods and schools are racially segregated because of historic and ongoing systematic discrimination embedded in policy and law (Harris, 1993; Rothstein, 2017). The College Board (2011) (p. i) describes Segment as “an Educationally Relevant Geodemographic Tagging Service” that enables universities to filter prospects based on the college-going characteristics of the high schools prospects attend or the neighborhoods prospects live in. We argue that student list products that build on existing patterns of segregation are likely to reinforce historical race-based inequality in educational opportunity.

To build Segment, College Board integrates information about test-takers and their neighborhood and school – including historical college going behavior. These data are grouped by high school and grouped by neighborhood (census-tract). Next, cluster analysis is used to “to group the 33,000+ high schools and 44,000 neighborhoods into 29 unique high-school types and 33 unique neighborhood types” (The College Board, 2011, p. 4), resulting in high school (HS) clusters HS:51-HS:79 and educational neighborhood (EN) clusters EN:51-EN:83. When buying names, a Segment customer may purchase prospects who scored within a particular range on the SAT, and live in a particular set of metropolitan areas, and who are associated with particular combinations of neighborhood and high school cluster (e.g., neighborhood cluster EN:73 and high school categories HS:65 or HS:70).

Table 5 and Table 6, recreated from The College Board (2011), show the characteristics of Segment neighborhood clusters and school clusters, respectively. These clusters are highly correlated with both racial and income demographics. For example, neighborhood cluster EN78 is 26% nonwhite and has median income of $134,400 while neighborhood cluster EN:71 is 97% nonwhite and has median income of $42,661.

We analyze 8 orders by a public research university that utilized Segment filters and specified very similar academic criteria across orders. These eight orders were made between February 2018 and April 2020, targeted 2019-2023 high school graduating classes, and resulted in 131,562 purchased prospects. All eight orders filtered on prospect GPAs ranging from a low of B- to a high of A+. The orders specified minimum PSAT/SAT scores ranging from 1220-1240 and maximum PSAT/SAT scores of 1450.[7] Prospects were also geographically filtered across State/CBSAs and segments. Several large CBSAs were consistently targeted across orders (including but not limited to Atlanta, New York, Philadelphia, Boston, Washington D.C., Detroit, Phoenix, Miami, Orlando, Baltimore, Denver, Raleigh).

All eight orders filtered on the same combination of Segment high school and neighborhood

[7]Five orders specified a minimum of 1240 on the SAT or PSAT and a maximum of 1450 on the SAT or PSAT; One order specified a minimum of 1230 on the SAT or PSAT and a maximum of 1450 on the SAT or PSAT; two orders specified a minimum of 1240 on the SAT or 1220 on the PSAT and a maximum of 1450 on the SAT or PSAT

Table 5: Filter by neighborhood segments

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

Table 6: Filter by high school segments

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

clusters, as follows:

- Neighborhood cluster 51, with any high school cluster
- Neighborhood cluster 53, with high school cluster 70
- Neighborhood cluster 58, with any high school cluster
- Neighborhood cluster 60, with high school clusters 65, 70, or 79
- Neighborhood cluster 61, with high school cluster 65
- Neighborhood cluster 63, with high school clusters 68 or 70
- Neighborhood cluster 69, with high school clusters 65 or 79
- Neighborhood cluster 70, with high school clusters 65, 68, 70, or 75
- Neighborhood cluster 73, with any high school cluster
- Neighborhood cluster 78, with high school cluster 66
- High school cluster 79, with any neighborhood cluster

Table 5 and Table 6 show that selected neighborhood and high school clusters – highlighted in blue – tended to have a higher income and a lower percentage of non-white students than clusters that were not selected, although this was not true across all selected clusters.

Figure 26 compares racial and income the characteristics of purchased prospects to the characteristics of all high school students. We show four metropolitan areas, where many prospects were purchased: New York (27,932 prospects purchased, rank #1), Los Angeles (12,307 prospects purchased, rank #2), Philadelphia (9,126 prospects purchased, rank #3), Washington, DC (5,728 prospects purchased, rank #4). For each metropolitan area, we show two figures: on the left column, we show the racial composition of purchased prospects living in the metropolitan area compared to the racial composition of all public high school students in the metropolitan area; on the right column, we show the income of purchased prospects living in the metropolitan area – defined as the average median household income of prospects' home zip codes– compared to the overall median income of the metropolitan area.

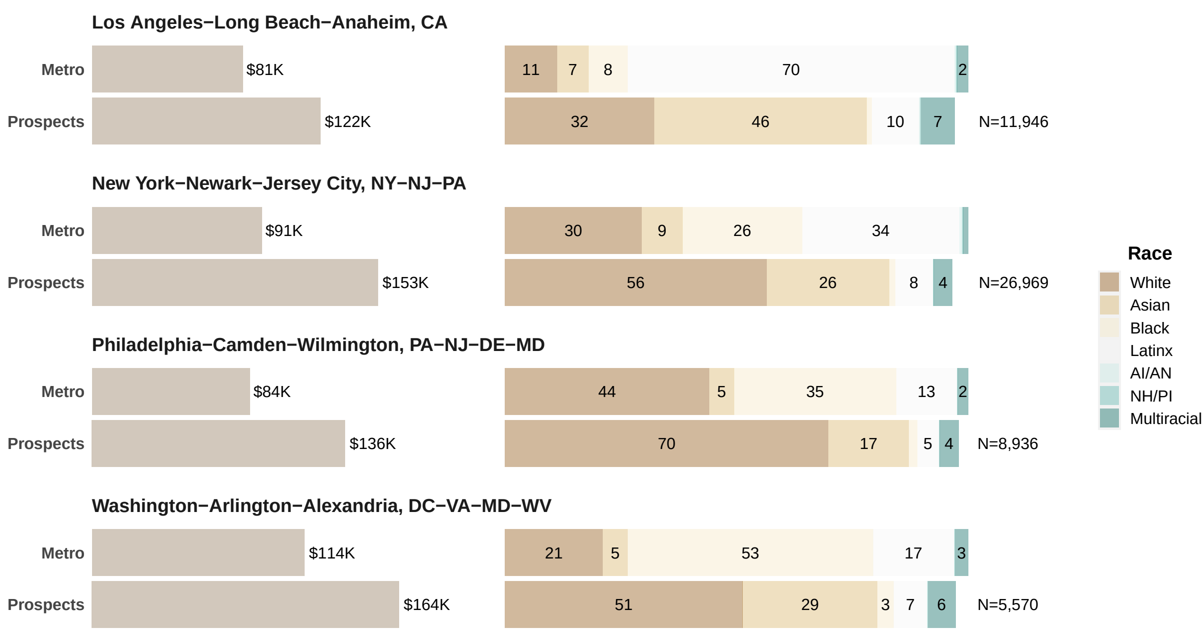
For New York, Figure 26 shows White and Asian students comprised 56.5% and 26.5% of purchased prospects, respectively, compared to 36.7% and 11.7% of students in public high schools. By contrast, Black and Latinx students comprised jut 1.31% and 8.04% of purchased prospects, respectively, compared to 17.8% and 31.7% of students in public high schools. Furthermore, purchased prospects lived in zip codes that were much more affluent – an average of $153,000 – than the overall New York metropolitan area median income of $91,000.

Figure 26 shows similar patterns for race in other three metropolitan areas. The race results for Philidelphia were particularly egregious, with Black and Latinx students representing

25.3% and 12.4% of public high school students, respectively, but only 1.81% and 4.60% of purchased prospects. Wide income disparities were present across metropolitan areas. In Washington, DC, purchased prospects lived in zip codes with an average median household income of $164,000 compared to $114,000 for the metropolitan area as a whole.

To what extent are these income disparities driven by the use of geodemographic Segment filters versus the other filters (e.g., SAT/PSAT score ranges) utilized in these orders? Unfortunately, the data we obtained via public records requests cannot address this question. What we can say is that the racial and income patterns observed in these orders are unacceptable. The use of geodemographic Segment filters may have contributed to these patterns. In the future, policymakers and researchers should obtain the data necessary to rigorously investigate the extent to which Segment filters cause racial, socioeconomic, and geographic disparities in purchased prospects.

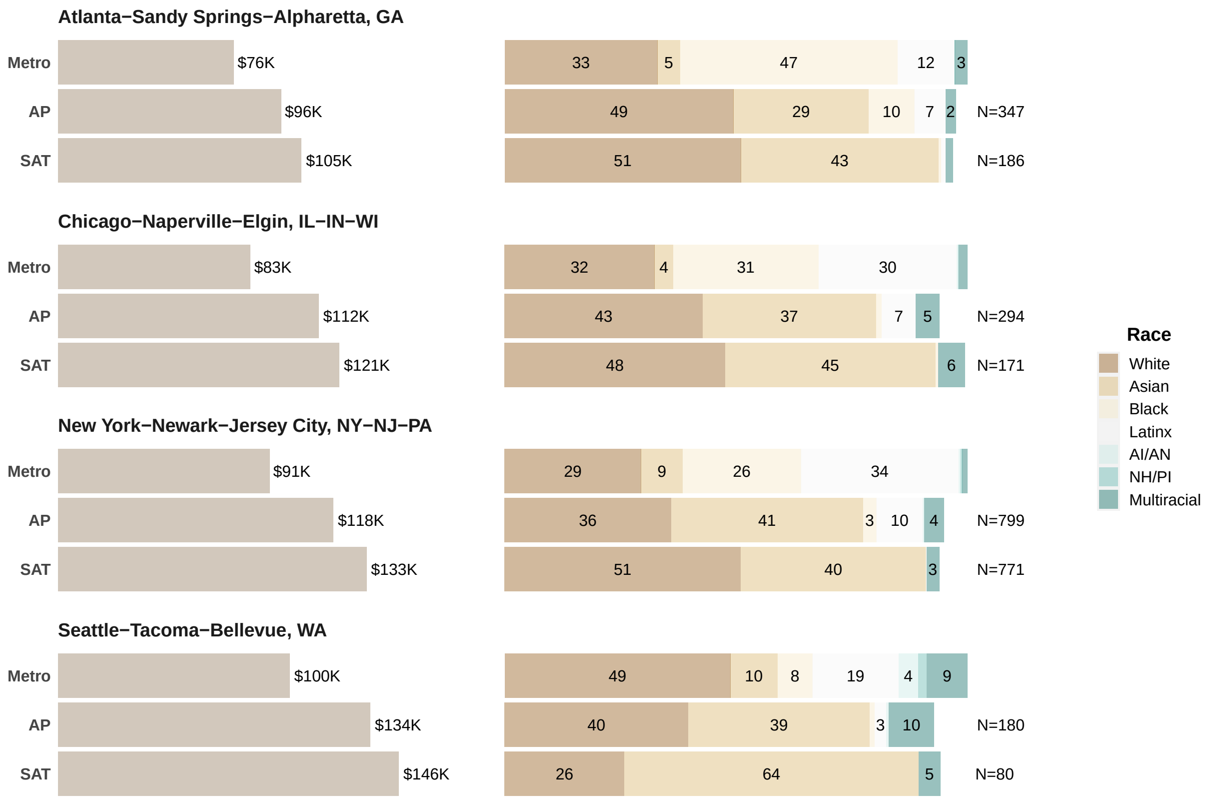
Figure 26: Segment deep dive



4.3.5 Women in STEM

Two research universities in the study made orders targeting prospects who are women interested in science, technology, engineering, and math (STEM). Orders by one university targeted women interested in STEM via two different filter patterns. The first pattern used SAT scores, GPA (ranging from a low of B and high of A+), a state filter (in-state versus out-of-state), and prospects' self-reported intended major. SAT score filters for these orders ranged from 1200 to 1600 for in-state prospects and 1300 to 1600 for out-of-state prospects.

Figure 27: Women in STEM deep dive



The second pattern also used the same GPA and state filters, but STEM interest was proxied via AP test scores. Orders for in-state prospects filtered for scores ranging from 3 to 5 on AP STEM tests.[8] Orders for out-of-state prospects filtered for scores ranging from 4 to 5 on AP STEM tests.[9]

In order to analyze in-depth patterns in the racial and economic characteristics of prospects that result from the combination of achievement, geographic, and gender filters used to target women interested in STEM, we analyze the resulting student lists from Women in STEM orders for four different metropolitan areas. The university made a total of 11 orders in March 2020 targeting women in STEM, which resulted in 12,938 prospects purchased. Six of the 11 orders targeted out-of-state prospects, with three orders using SAT scores plus major interests and three orders using AP scores. In-state prospects were targeted across five orders, three of which used AP scores and two of which used SAT scores with major interests.[10]

[8] AP STEM Tests included Biology, Chemistry, Computer Science (A & P), Environmental Science, Calculus (AB & BC), Physics (1, 2, B, C: Electricity and Magnetism, & C: Mechanics) and Statistics

[9] Orders by the second university also generally followed these patterns, although SAT and AP score ranges differed slightly. The second university also targeted women interested in engineering majors through the use of segment filters at the high school and neighborhood levels in combination with some achievement filter (e.g., PSAT, SAT, GPA).

[10] Three of the 11 orders resulted in student lists with zero prospects. Two of these zero prospect orders

Because nearly 85% of student lists from Women in STEM orders resulted in out-of-state prospects (N=10,668), we select four out-of-state metropolitan areas and compare prospects to the characteristics of public high school women students in those metropolitan areas. The four out-of-state metropolitan areas were selected based on where the greatest number of prospects were purchased and based on regional variation: New York (1,663 prospects purchased, rank #1), Atlanta (548 prospects purchased, rank #2), Chicago (485 prospects purchased, rank #3), and Seattle (279 prospects purchased, rank #11).

Figure 27 compares racial and income characteristics of purchased prospects to the characteristics of all public high school women students in each metropolitan area. For each metropolitan area, we show two figures. The figure on the left column provides the average median household income for the overall metropolitan area, for prospects purchased using AP scores, and prospects purchased using SAT scores. Prospect-level economic characteristics are measured by taking the average median household income of all prospects' home zip codes. The figure on the right column provides the racial/ethnic composition of all public high school women students in the metropolitan area, of prospects purchased using AP scores, and of prospects purchased using SAT scores.

For example, Figure 27 shows the overall median household income for the Atlanta metropolitan area is $76,000. Relative to this overall median household income, Women in STEM prospects purchased by the university across both types of orders are more affluent. Purchased prospects that scored a 4 or 5 on an AP STEM exam live in Atlanta zip codes where the average median household income is $96,000. Whereas purchased prospects that scored a 1200 to 1600 on the SAT and indicated an interest in STEM majors live in Atlanta zip codes where the average median household income is $105,000.

Women in STEM prospects are also consistently more affluent than their overall metropolitan areas across Chicago, New York, and Seattle, with prospects purchased through SAT filters having the highest overall incomes. For Chicago, prospects purchased via AP and SAT filters have average median household incomes $29,000 and $38,000 greater than the overall median household income across the metropolitan area ($83,000), respectively. This difference in median household income between the overall metropolitan area and prospects purchased via AP ($34,000) and SAT filters ($46,000) is most pronounced for Seattle.

Figure 27 also shows the racial/ethnic composition of prospects relative to public high school women students in their metropolitan areas. For example, public high school women students in New York are 29% White, 9% Asian, 26% Black, and 34% Latinx. However, Women in

filtered for in-state prospects, one via AP scores and the other via SAT scores. The third zero prospect order filtered for out-of-state prospects via AP scores.

STEM prospects from New York that scored a 4 or 5 on an AP STEM exam purchased by the university are 36% White, 41% Asian, 3% Black, 10% Latinx, 4% multiracial. Only 2 women in STEM prospects in New York City purchased via AP scores identified as Native American. These racial disparities are most pronounced in orders using SAT scores. New York purchased prospects that scored a 1200 to 1600 on the SAT and indicated an interest in STEM majors are 51% White, 40% Asian, and 6% multiracial. Only one woman in STEM prospect purchased from New York City via SAT scores identified as Latinx, with zero prospects identifying as Black or Native American.

The racial/ethnic disparities between Women in STEM prospects relative to the public high school women student population in their respective metropolitan areas are most pronounced in Atlanta. Public high school women students in Atlanta are 33% White, 5% Asian, 47% Black, 12% Latinx, and 3% multiracial. However, prospects purchased via AP scores are 49% White, 29% Asian, 10% Black, 7% Latinx, and 2% multiracial. Most concerning, prospects purchased via SAT scores and STEM major interests are 51% White, 43% Asian, 0.5% Black (1 student), 1% Latinx (2 students), and 2% multiracial.

Similar patterns in racial/ethnic composition of Women in STEM prospects are also evident across Chicago and Seattle. For instance, Black women make up only 1% of prospects purchased in Chicago across both AP and SAT orders despite making up nearly one-third (31%) of public high school women students in the metropolitan area. On the other hand, proportions of White Women in STEM prospects purchased in Seattle tended to be lesser than the overall public high school women student population in the metropolitan area, but had much larger proportions of Asian students.

4.3.6 Targeting URM Students

College Board and ACT student list products enable universities to target prospects who identify with particular ethnic and racial groups. In our sample, race ethnicity filters were utilized almost exclusively by research universities. As shown in Figure 16, commonly observed filters were Latinx/Black/AIAN (N=19 purchases) and Asian/White/NHPI (N=19). A smaller number of purchases filtered for particular racial groups (e.g., NHPI) or particular ethnicities (e.g., Latinx). Similar to Women in STEM orders reviewed above, universities may be filtering by race/ethnicity when purchasing student list as means to overcome the historical exclusion of Students of Color in higher education and promote racial diversity in college access, particularly given the trend away from race-conscious admissions policies. We explore whether and to what extent the use of filter combinations to solve inequities in one problem

Figure 28: Targeting students of color, race categories

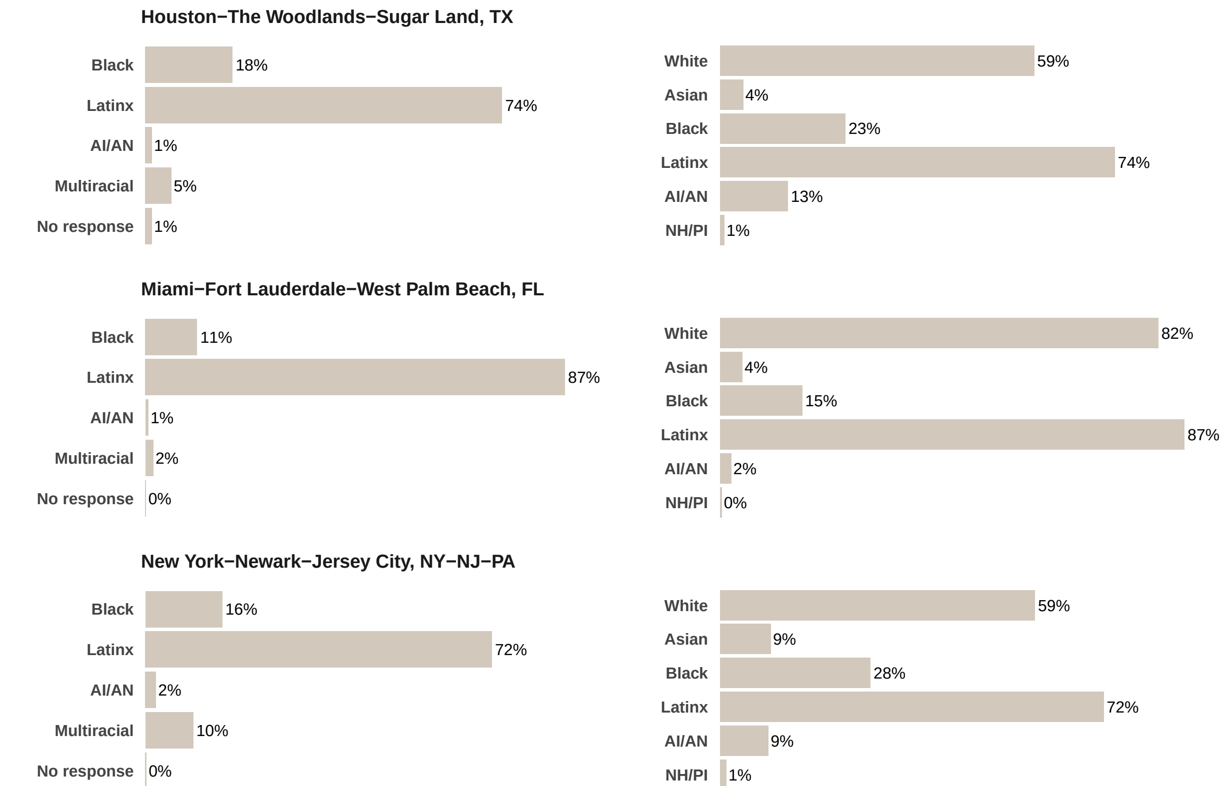
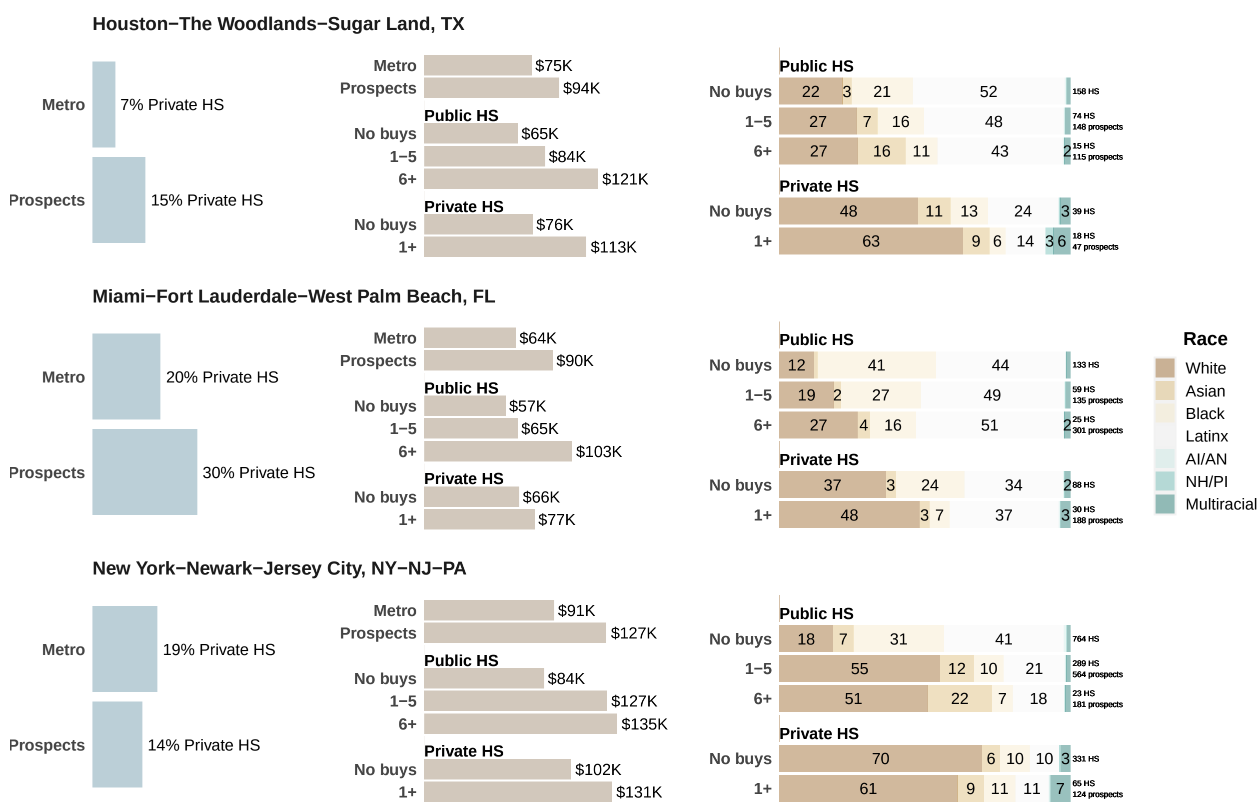


Figure 29: Targeting students of color, purchased prospects



(e.g., lack of racial diversity in college enrollments) may lead to other problematic inequities (e.g., only include Students of Color with extraordinarily high test scores or Students of Color from predominantly White schools and communities).

This analysis draws from a student list purchase named "NR 2021 SAT URM 1200-1380" that targeted students from the high school class of 2021, from 28 states (excluding CA), who had SAT scores between 1200 and 1380, a high school GPA between "B" and A+, and who identified as Latinx/Black/AIAN. Our data indicate that this purchase yielded 5,678 prospects. Our analyses examine the extent to which these prospects tend to come from wealthy, predominantly white communities and schools.

We analyze the three core based statistical areas (CBSAs) with the largest number of purchased prospects: New York-Newark-Jersey City, NY-NJ-PA (N=949 prospects); Miami-Fort Lauderdale-West Palm Beach, FL (N=671 prospects); and Houston-The Woodlands-Sugar Land, TX (N=371 prospects).

Figure 28 examines the race and ethnicity of purchased prospects in each of the three CBSAs. The left column utilizes the College Board "derived aggregate race/ethnicity" variable, which allocates each student to one race/ethnicity category among White, Asian, Black, Latinx, American Indian/Alaska Native, or Native Hawaiian/Pacific Islander. For example, if a student selected a Hispanic ethnicity and White as their race, these students were defined as Latinx on the left hand column of Figure 28. However, a given student may identify with multiple ethnicities and multiple racial groups. The right column shows the percent of prospects who identify with each racial group, which is why percent totals sum to greater than 100. Focusing on the aggregate race/ethnicity column (left), prospects included in student list orders targeting Latinx/Black/AIAN students included 11% to 18% Black students, 72% to 87% Latinx students, 1% to 2% American Indian/Alaska Native students, and 2% to 10 % multiracial students (e.g., students who selected two race/ethnicities from which one was Latinx, Black, or American Indian/Alaska Native), across all three metropolitan areas.

Figure 29 describes the high schools these prospects attended. The left column examines attendance at public and private schools. For example, across the New York CBSA, 19% percent of high school students attended a private high school compared to 14% of purchased prospects. The middle column examines household income. Prospects purchased from New York lived in zip codes where the average income was \$127,000, considerably higher than median income of \$91,000 in the New York CBSA. New York public high schools with one to five purchased prospects and greater than six purchased prospects were located in zip codes where the average household income was \$127,000 and \$135,000, respectively, both of which are considerably higher than that of public high schools where no prospects were purchased ($84,000). The right column examines the race/ethnicity composition of public and private high schools. For example, New York CBSA public high schools where no prospects were purchased were, on average, 31% Black, 41% Latinx, 19% white, and 7% Asian. On the other hand, schools with one to five purchased prospects were on average, 10% Black, 21% Latinx, 55% white, and 12% Asian.

Results for Miami differed from New York. The differences in household income were less pronounced than the case of New York, although the largest disparity is seen in Miami public high schools with greater than six purchased prospects had an average household income of $103,000 relative to $57,000 for public high schools where no prospects were purchased. With respect to the racial composition of public schools, schools with at least one prospect purchased tended to enroll a higher number of Latinx students but a lower number of Black students than schools with no prospects purchased. At the same time 30% of prospects purchased from Miami attended a private high school and these private high schools tended to enroll relatively few Black students (7% of total enrollment) but a large number of Latinx students (37% of total enrollment).

Results for Houston show that purchased prospects also tended to live in relatively affluent communities. However, most purchased prospects (85%) attended public schools and public schools with at least one purchased prospect tended to enroll similar shares of Black and Latinx students as public schools with no purchased prospects.

Results for these three metropolitan areas suggests that purchases targeting URM students with relatively high standardized test scores tend to yield prospects who live in wealthy communities and attend schools in wealthy communities. However, the extent to which these prospects attend predominantly White high schools seems to differ by metropolitan area, partly a factor of local patterns of school segregation. In New York – and also Philidelphia and Chicago (results not shown) – Black and Latinx prospects included in purchased student lists tended to attend predominantly white high schools, while public schools with with zero purchased prospects enrolled predominantly non-white students. By contrast, in Miami and Houston – and also Atlanta – Black and Latinx prospects included in purchased students lists attended schools with larger shares of Black and Latinx students. However, even in these metropolitan areas, schools with at least one purchased prospect tended to have much lower enrollment of Black students than schools with zero purchased prospects.

5 Discussion

Recent research suggests that student lists are surprisingly important for the college access outcomes and the graduation outcomes of millions of students each year (Howell, Hurwitz, Mabel, & Smith, 2021; Moore, 2017). Jaquette, Salazar, & Martin (2022) provide a conceptual analysis of the student list business. We argue that the College Board and ACT student list products, which have dominated the market for decades, systematically exclude students in two ways. First, the underlying databases exclude non-test-takers. Test-taking rates differ by race and by class, leading to differences in which prospects are included in student list products and, in turn, differences in who is targeted by universities. Second, the search filters available on student list products enable universities to target certain prospects and exclude others.

Although CB began selling names fifty years ago (Belkin, 2019), this report is the first empirical analysis of student list purchases. We collected data by issuing public records requests to public universities in four states. This was a challenging and imperfect data collection. At the conclusion of this first set of analyses, we have more questions than answers. Paraphrasing Khan (2012, p. 362), we call it a start.

Research question 1 asks, which filter criteria were selected in student lists purchased by universities in our sample? The most commonly specified filters were high school graduating class, SAT or PSAT score range, high school GPA, state and zip code. However, each order specified multiple filters. At minimum, most orders specified high school graduating class, one or more academic achievement filters, and one or more geographic filters. Only 10% of orders by research universities filtered on AP score. The orders we analyzed were mostly purchased prior to the Covid Pandemic, which catalyzed the test-optional movement. Universities may respond to the decline in SAT/PSAT test-takers by filtering on AP score, which raises equity concerns due to inequality in which high schools offer robust AP curricula [CITE AWILDA?].

Research question 2 asks, what are the characteristics of prospects included in student lists purchased? The ma/doctoral universities in our sample primarily purchased in-state prospects. Across all ma/doctoral universities, in-state prospects were 46% white, 10% Asian, 26% Latinx, and 8% Black. In-state prospects by research universities were 41% white, 14% Asian, 32% Latinx, and 5% Black. Similar to our analysis of off-campus recruiting visits (Salazar, Jaquette, & Han, 2021), research universities in our sample purchased many more out-of-state prospects than in-state prospects. These out-of-state prospects were more affluent than in-state prospects and were more likely to identify as white and Asian in-state prospects, and were somewhat more likely to attend a private school than in-state prospects.

However, data collection challenges yielded a non-random sample – requiring a case study research design – limiting the external validity of findings for RQ1 and RQ2, which were substantially driven by universities that purchased many lists and many prospects. We also collected data about student lists purchased from ACT and other vendors (and also data about off-campus recruiting visits), but have lacked the capacity to process and analyze these data.

Policymakers should commission a more systematic data collection of student list purchases – and other recruiting interventions – in order to develop externally valid evidence about university recruiting behavior. A basic question is how student list purchases – number or orders, search filters, volume of names – differ by more granular typologies of university type. Other important questions include, to what extent do universities filter on five-digit zip codes? Are filtered zip codes highly correlated with race and income? Do test-optional universities continue to filter on SAT/ACT test scores? Have universities responded the decline in test-takers by filtering on AP test scores and What are the equity consequences of filtering by AP score? To what extent do universities purchase student lists to reach out to prospects not being targeted by other interventions (e.g., off-campus recruiting visits)? Finally, many universities outsource student list purchases to an enrollment management consulting firm (e.g., EAB, Ruffalo Noel Levitz). Do certain firms tend to purchase lists that raise concerns for equality of opportunity?

Research question 3 asks, what is the relationship between student list filter criteria and the characteristics of purchased prospects? This question is about student list products rather than university behavior. Here, we are on firmer ground from an external validity perspective because a particular set of filter criteria yields the same set of prospects regardless of which university places the order.

Analyses for RQ3 centered on “deep dives” of four commonly observed or thematically important order combinations. First, we show that filtering for affluent zip codes causes racial diversity to decline substantially. Second, analyses of the Segment product revealed troubling patterns of racial and socioeconomic exclusion. However, we could not assess the extent to which these patterns were driven by Segment versus other filters utilized (e.g., SAT score). Future research should examine which combinations of Segment neighborhood and school clusters reproduce racial redlining (and reverse-redlining in the case of for-profits) and/or systematic exclusion of rural student. Third, orders that filtered for unerrepresented students of color with relatively high test scores tended to target affluent students, who often attended predominantly white high schools. Finally, our analysis of orders that target females based on AP score suggest that the Women in STEM movement should do some soul searching about its relationship to race and class.

Cost of efficiency. Over the past decade, the set of search filters offered by College Board and ACT have become more elaborate (e.g., Encoura Enrollment Predictor, College Board Environmental Attributes. The rationale for new search filters is efficiency, meaning that universities only purchase the names of "best-fit" prospects who are likely to apply and enroll. For example, College Board Student Search promises to "create a real pipeline of best-fit prospects" [CITE] while ACT Encoura uses the tag-line "find and engage your best-fit students" [CITE]. The set of search filters now available in College Board and ACT student list products enable universities to execute fine-grained purchases that target particular prospects with pin-point accuracy, while excluding all others.

We also observe this emphasis on efficiency in the marketing materials of enrollment management consulting firms, which purchase student lists on behalf of universities. For example, Ruffalo Noel Levitz states the "RNL Student Search and Engagement" product enables universities to "target the right students in the right markets" by making "the most efficient name purchases using predictive modeling" (Ruffalo Noel Levitz, 2021). Fire Engine Red states that their "student search modeling" product "can save your school money, by helping you purchase only the names of students who are most likely to apply and enroll" (Fire Engine RED, 2021, para. 3).

The emphasis on efficiency – in both the design and usage of student list products – has important consequences for equality of opportunity. We argue that talented prospects are excluded in the name of efficiency. Our analyses show that filtering for affluent zip codes causes racial diversity to plummet. Geodemographic filters like Segment and Environmental Attributes exclude prospects based on the historical college-going behaviors of students from the same neighborhood or school. From an equality of opportunity perspective, what is the justification for student list products that allow universities to target prospects from one zip code and exlude prospects from the zip code across the street? What is the justification for products that allow universities to filter prospects based on the past behavior of their peers?

Universities care about efficient name buys only because the price of names is so high. In 2021, College Board charged $0.50 per name (The College Board, 2021). In 2022, College Board followed the example of ACT by transitioning to a subscription pricing model, in which higher tier plans offer more sophisticated filters (e.g., Segment Analysis Service, Interest in My Peers) and services. Jaquette, Salazar, & Martin (2022) argues that the test-optional movement will end the College Board and ACT student list oligopoly. For-profit vendors (e.g., EAB, PowerSchool) are poised to capture market share ceded by College Board and

ACT. However, we suspect that this transition will cause the price of names to increase, because these for-profit vendors have learned to maximize profit by providing names only to universities that pay for expensive consulting and/or subscription services.

The national voter databases created by U.S. political parties offer an interesting counter-example to student lists. The basic input to these databases consists of state and local voter files, which are essentially free public records (Culliford, 2020). By contrast, the basic inputs for student lists are propietary and they are expensive, which creates the rationale for efficiency. In *Student List Policy*, we propose a "public option" student list product developed by a consortium of states, based on data from statewide longitudinal data systems. The "names" of students who opt in would be provided for free to eligible postsecondary institutions, thereby eliminating the rationale for efficient name buys that target some prospects but not others.

6 Appendix

Figure 30: Example College Board order summary

6/17/2021 My Searches, Orders & Files: College Board Search

[redacted]

My Searches, Orders & Files

2020PSATNM 1470-1520 CO,IL,NY,CT,WA,VA,MD,CA,MA,NJ

Print

Created by: [redacted] last updated: 1/8/19

Order Number 448006

Order Summary

Order type:	Name License / Single Order	**Name license status:**	Fulfilled
Search owner:	[redacted]	**Start date:**	Tue, Jan 08, 2019
Search created:	1/7/19	**End date:**	Tue, Jan 08, 2019
Submitted by:	[redacted]	**Projected volume:**	7,551 names
		Maximum volume:	7,551 names
		Volume to date:	7,541 names
Submitted:	1/8/19	**Runs to date:**	1 runs

Billing Details

Payment type: Bill Me

Billing address: [redacted]

Delivery Options

File recipients: [redacted]

Sorting sequence: Alphabetic

Print format: Upper and lowercase

File format: Tab Delimited - .tsv

Delivery frequency: N/A

Search criteria

Criteria	Selections
Graduating Class	**Research & License** 2020 HS grad class **New prospects** Include only new students not included in my other orders
College Board Exams	**Filter by** Student's highest exam scores **Exam scores** PSAT/NMSQT Total Score 1470 - 1520

https://pastud-prod.msss-prod.collegeboard.org/pastudentsrch/report-file-summary.htm?savedSearchId=460675 1/2

6/17/2021 My Searches, Orders & Files: College Board Search

Criteria	Selections
Geography	**U.S states & territories** Connecticut Illinois Massachusetts Maryland Washington New York Virginia Colorado New Jersey View all
High School Academic Performance	**Grade point average** High: A+ Low: B-
Email & Postal Address Preferences	Email and Mailing Address

Runs

Run Number	Date	Volume	Cost
1	1/8/19	7541	$3,393.45

https://pastud-prod.msss-prod.collegeboard.org/pastudentsrch/report-file-summary.htm?savedSearchId=460675 2/2

7 References

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

Campbell, A. (2017). Higher education marketing: How to master your admissions funnel. Retrieved from https://hop-online.com/blog/higher-education%20-marketing-admissions-process/

College Board. (2022). *How student search service works for you*. College Board. Retrieved from https://studentsearch.collegeboard.org/

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

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, *14*(4), 532–550. https://doi.org/10.5465/amr.1989.4308385

Fire Engine RED. (2021). *Data services: Search modeling*. Fire Engine RED. Retrieved from https://www.fire-engine-red.com/data-services/

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

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

Jaquette, O., Salazar, K., & Martin, P. (2022). *The student list business*. New Orleans, LA: ACCEPT. Retrieved from #

Khan, S. R. (2012). The sociology of elites. *Annual Review of Sociology*, *38*, 361–377. https://doi.org/10.1146/annurev-soc-071811-145542

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

Rothstein, R. (2017). *The color of law: A forgotten history of how our government segregated America*. Liveright Publishing.

Ruffalo Noel Levitz. (2021). RNL student search and engagement. Retrieved from https://www.ruffalonl.com/enrollment-management-solutions/building-demand/student-search-and-engagement/

Salazar, K. G., Jaquette, O., & Han, C. (2021). Coming soon to a neighborhood near you? Off-campus recruiting by public research universities. *American Educational Research*

Journal, *58*(6), 1270–1314. https://doi.org/10.3102/00028312211001810

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

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

The College Board. (2021). Pricing and program updates coming to search this fall. Retrieved from https://allaccess.collegeboard.org/pricing-and-program-updates-coming-search-fall