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

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1 Introduction

On March 8th 2020, a selective public research university ordered several "student lists" from College Board. Student lists contain the contact information of prospective students. Several orders targeted women in STEM fields, including an order given the title "NR 2021 Female AP STEM," which targeted nonresident high school students from 26 states, who identified as female, were in the high school class of 2021, had a high school GPA of B to A+, and received a 4 or higher on an AP exam in a STEM subject (e.g., calculus, biology, chemisty, computer science, statistics). Another order titled "NR 2021 Female SAT STEM" targeted the same prospects except the AP exam search filter was replaced with scoring between a 1300 and 1600 on the SAT [MAYBE CUT THIS SENTENCE].

The university purchases lists of prospective female STEM students in order to overcome the under-representation of women in STEM degree programs, which has been a nationwide policy concern for decades [CITE]. However, an analysis of the purchased prospects suggests that efforts to overcome one problem are creating other problems. Figure X shows recruiting female STEM prospects based on AP scores yields a set of prospects from almost exclusively affluent communities and they are recruiting prospects who identify as white or Asian but not prospects who identify as Black or Latinx. [ONE OR TWO SENTENCES GIVING RESULTS]. These results are consistent with socioeconomic and racial disparities in access to AP coursework.

Although prior research suggests that student lists have a surprisingly large effect on college access (Howell, Hurwitz, Mabel, & Smith, 2021; Moore, 2017; Smith, Howell, & Hurwitz, 2021), the women in STEM vignette highlights concern of who is being included. We argue that student list products exclude students in two ways. First, universities cannot purchase the contact information of prospects who are not included in the underlying database. In general, College Board and ACT student list products only include test-takers, but test-taking rates differ substantially across race and class (Hyman, 2017).[1] Second, the "search filters" on student list products enable universities to choose the prospects included in a purchase. While 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 systematically exclude protected classes and other populations that are underrepresented in higher education (e.g., rural students).

Prior research has not examined which filter criteria universities select when purchasing student lists, what are the characteristics of purchased prospects, or the relationship between filter criteria and student characteristics. 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?
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?

2 Background

This section provides relevant background information by situating student lists within the recruiting process, reviewing recent research on the relationship between student lists and student outcomes, and explaining how universities buy lists and what information they contain. We focus on lists sold by College Board, which are the focus of empirical analyses.

2.1 Situating Student Lists within Recruiting

Similar to the visual metaphor of the "STEM pipeline," the "enrollment funnel" – depicted in in Figure 1 – is a conceptual model used in the enrollment management industry to describes stages in the process of recruiting students. The funnel begins with a large pool of "prospects" that the university would like to convert into customers. "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

[1] FOOTNOTE; ACT NRCCUA

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 convert admits to enrolled students.

Figure 1: The enrollment funnel

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 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.

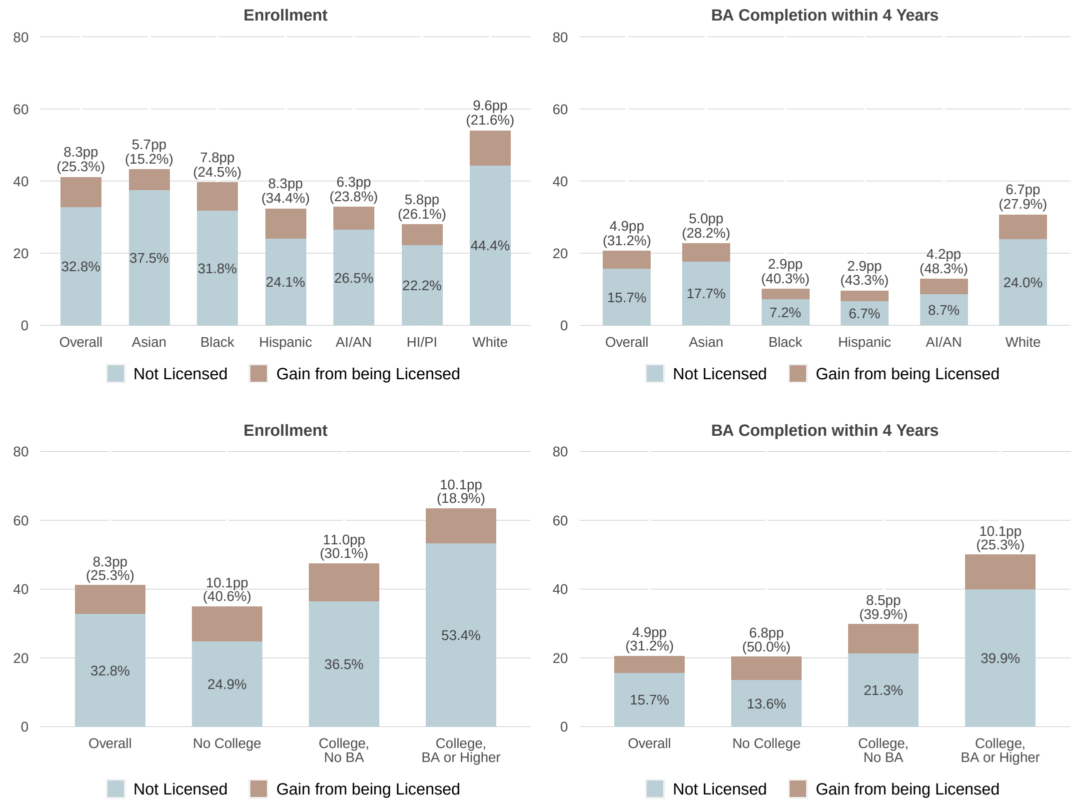
2.2 Student Lists and Student Outcomes

Research suggests that student lists substantially affect college access outcomes – and in turn degree completion outcomes – for millions of students each year. Howell et al. (2021) compared SAT test-takers who opted into the College Board Student Search Service – allowing accredited institutions to "licence" their contact information – and test-takers who opted out, after controlling for covariates. Figure 2 reproduces the main results. 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 (`=41.1-32.8`) percentage point difference and a 25.3 (`=(41.1-32.8)/32.8`) percent change in the relative probability of attending a 4-year college (for a similar analysis of ACT's Educational Opportunity Service (EOS) see Moore (2017)).

Figure 2 shows that participating in Search was associated with a larger percent change in the probability of attending a 4-year institution for students who identified as Black (24.5%`=(39.6-31.8)/31.8`), 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 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 institution. Howell et al. (2021) analyzed the four-year BA degree completion rates of SAT test-takers from the 2015 and 2016 high school graduation cohorts. Figure 2 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% (`=(20.6-15.7)/15.7`) 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 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 2: 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.

2.3 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 test takers to opt into the "Student Search Service," which enables "accredited colleges, universities, nonprofit scholarship programs, and nonprofit educational organizations" (**???**) to "license" their contact information. In fall 2021, the College Board Search product both charged $0.50 per name (The College Board, 2021).

How do universities purchase student lists from College Board Student Search Service and ACT's Encoura platform? Each purchased list is a subset of prospects drawn from the population of test-takers by specifying multiple search filters. (**???**) states that commonly specified search filters for ACT include high school graduation year, high school GPA, test score range (ACT or PreACT), gender, ethnicity, intended major, and geography (e.g., state, county, zip code) (**???**) [CHANGE THIS EXAMPLE TO ACT]. As a hypothetical example, a university could purchase a student list from ACT that consisted of all prospects who scored between 30 and 34 on the ACT, 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 recently began offering filters that enable universities to target prospects based on statistical models of the past behavior of similar or nearby prospects. [ADD LINKS/APPENDIX FIGURES SHOWING AVAILABLE SEARCH FILTERS FOR CB/ACT?]

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., ethnicity, race, gender, high school GPA, graduation year, high school code, intended major, first-generation status). The data template for an ACT student list can be found here and the template for a College Board student list can be found here. These fields represent a small subset of the information the testing agencies know about prospective students and contain little data about performance on assessments (e.g., SAT score). As we discuss below, College Board and ACT provide more detailed information to universities that pay for their enrollment management consulting services.

3 Data Collection and Research Design

This section describes, first, the data collection for the broader project. Second, 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 research project that would utilize public records requests to collect data about recruiting behavior from all public universities in four states, California, Illinois, Minnesota, and Texas.

Public records requests. We used public records requests to collect data about student lists purchased by public universities. Following several months of planning and pilot requests, we began issuing public records requests in February 2020. 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.[2]

For each student list purchased from 2016 through 2020 for the purpose of undergraduate recruiting, we requested two related pieces of data: the order summary, which specifies search criteria for the student list purchase; and the de-identified prospect-level list produced from the search criteria. Figure X shows an example of a College Board order summary.[3] In Figure X, the university purchased the contact information of prospects who CRYSTAL ADD TEXT. Figure X shows partial data from the de-identified 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) [CRYSTAL - ADD THESE FIGURES TO MAIN TEXT order summary data, and de-identified student list data].

Data collection sample. The data collection sample consists of all public universities in IL, MN, CA, and TX. 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. We also collected data from Arizona State University and Northern Arizona University.

Figures 3 and 4 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.

The Appendix discusses data collection challenges, successes, and lessons learned for future data collection efforts. Appendix Figure X-X reports the status of data collection for each

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

[3] Each recrods request letter also asked for data about off-campus recruiting visits

university in the data collection sample.

Figure 3: University by carnegie classification

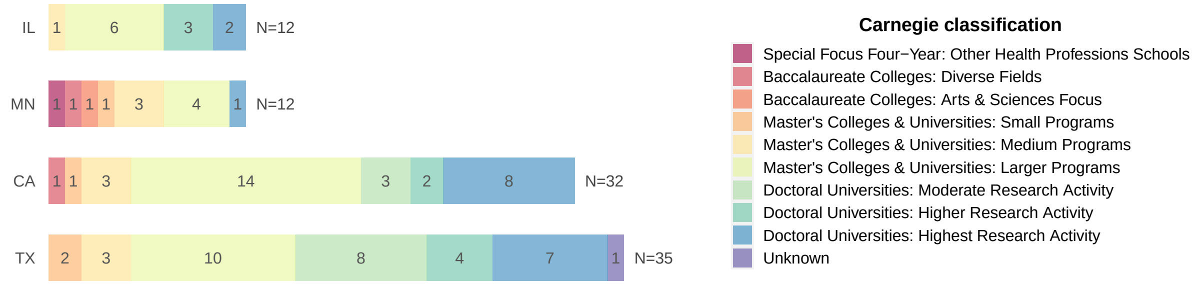
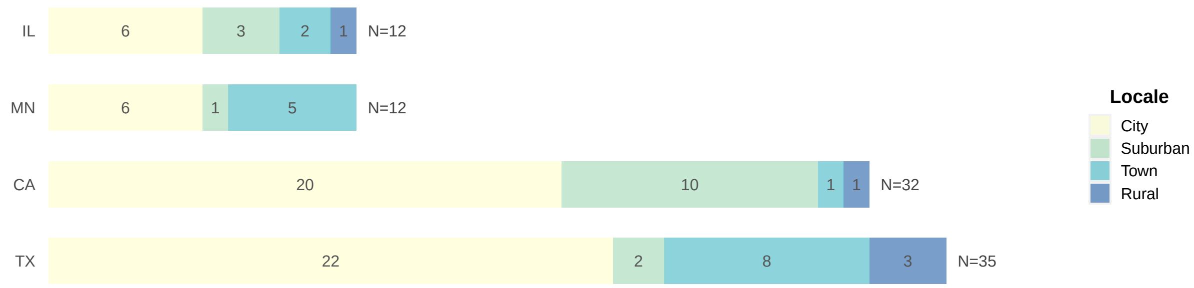


Figure 4: University by locale



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.

QUESTION OJ 4/26/2022 - SHOULD WE DEFINE ANY VARABLES HERE? IT IS NECESSARY TO EXPLAIN RACE/ETHNICITY VARIABLES AT LEAST. FOR NOW, I PUT A PARAGRAPH ABOUT RACE/ETHNICITY VARS AT BEGINNING OF RQ2 RESULTS, BUT IT IS SORT OF AWKWARD THERE. WE COULD SAY SOMETHING LIKE "WE DEFINE RACE/ETHNICITY VARIABLES HERE BUT OTHER VARIABLES CAN BE DESCRIBED LATER CUZ THEY DO NOT REQUIRE A SUBSTANTIAL EXPLANATION]. OR WE COULD JUST INCLUDE DESCRIPTION OF RACE/ETHNICITY VARIABLES IN AN APPENDIX.

3.2 Research Design

Decisions about research design and research questions depended substantially on the results of our data collection.

Analysis sample. This report analyzes student lists purchased from 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 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 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/KARINA - FILL IN NUMBERS IN TEXT IN THS PARAGRAPH AND ABOVE; ALSO NUMBERS DON'T MATCH BETWEEN TEXT AND TABLE]

Figure 5 shows the number of student lists purchased by Carnegie Classification and state. Figure 6 shows the number of prospects purchased by Carnegie Classification and state.

Figure 7 presents the 838 total orders analyzed in this report by university type and total students purchased. The 838 orders were purchased across 16 universities. The six master's universities in the study made the majority of order purchases (N=307), while research universities made 530 orders and the only baccalaureate university in the study made one order.

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 versus 2,382).

Research questions and analyses. 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

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

Figure 5: Summary of orders purchased by carnegie classification

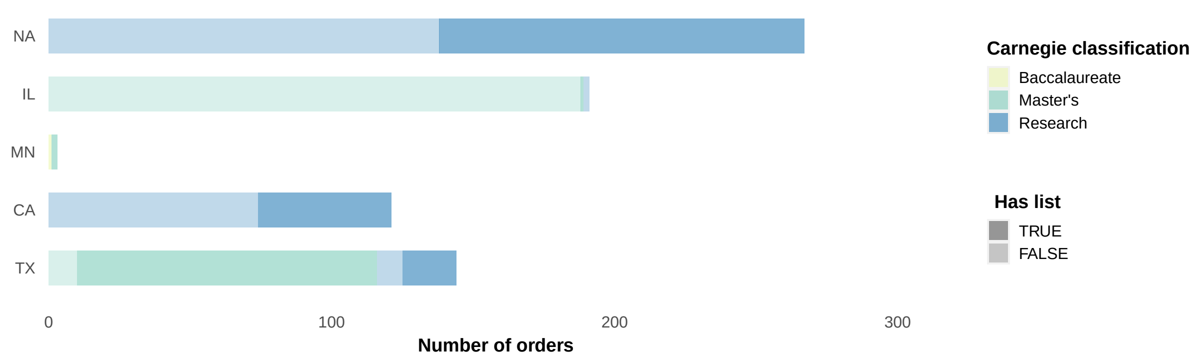


Figure 6: Summary of prospects purchased by carnegie classification

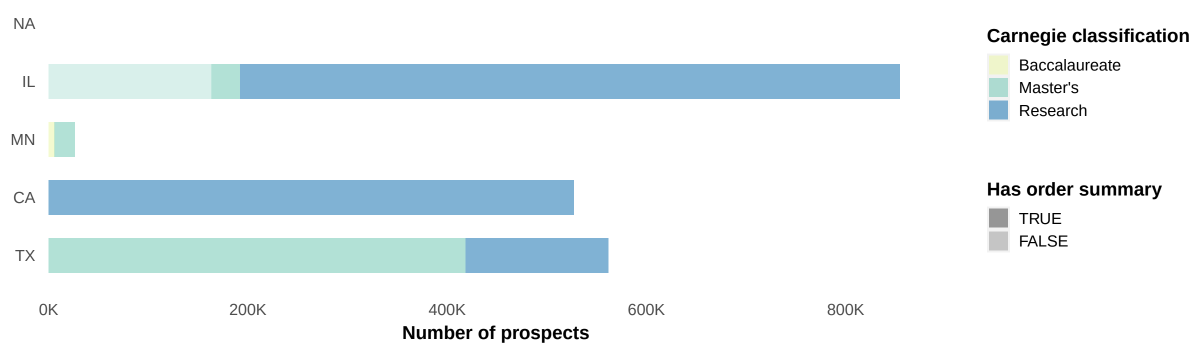


Figure 7: Orders purchased by carnegie classification

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 should investigate the relationship between the filters chosen for a particular student list purchase and who is 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.

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

Research question 1 asks, which filter criteria were selected in student lists purchased by universities in our sample? We first describe broad pattens 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). 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 8 shows how often filters were used by university type. Note that student list purchases typically filter on multiple criteria. Figure X shows the prevalence of individual filters, not how often they are used in combination with other filters.

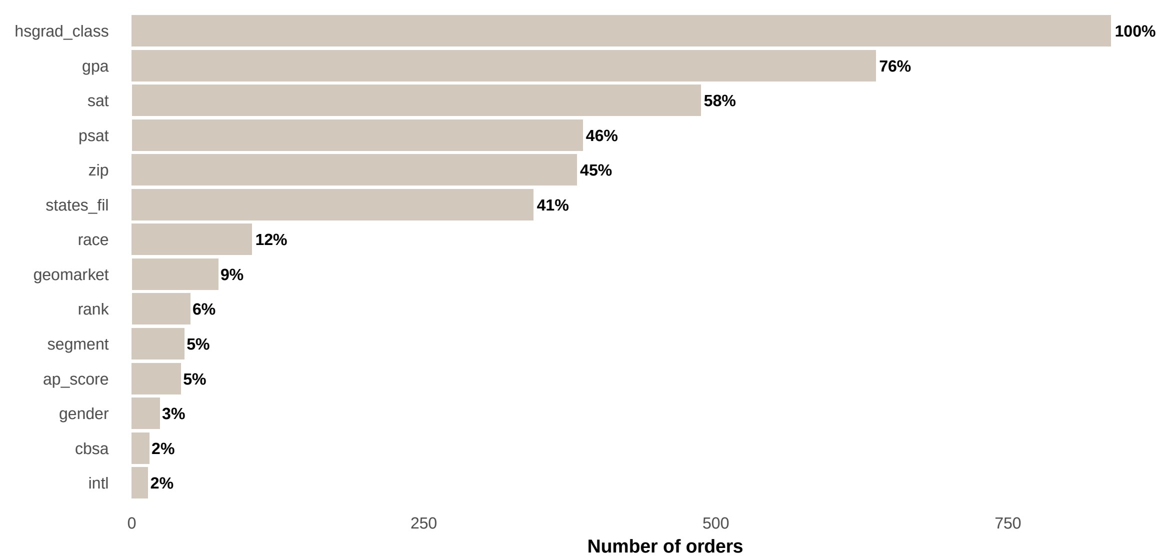
All orders by both research universities (n = 377) [CHECK] and ma/doctoral universities (n = 458) filtered by high school graduation class. Commonly used academic filters across university type include GPA, SAT, and PSAT. Compared to ma/doctoral universities, research universities were somewhat less 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 (12% of orders) and AP score (10% of orders), but few ma/doctoral orders utilzied these filters.

Orders by ma/doctoral versus research universities differed across geographic filters. Nearly 77% of orders by research universities used a state filter but only 11% of orders by ma/doctoral universities filtered for entire states. 83% of 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.

Finally, ma/doctoral universities did not utilize demographic filters. For research universities, about 27% or orders filtered by students' race/ethnicity and 6% of orders filtered on gender.

[WHAT ABOUT FILTERS FOR STUDENT PREFERENCES LIKE INTENDED MAJOR, COLLEGE SIZE/TYPE? WERE THESE JUST RARELY UTILIZED OR WE DIDN'T CODE THE DATA? IF THE LATTER, WE SHOULD STATE THIS]

Figure 8: Filters used in order purchases



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+."[4] However, Figure X 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

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

Table 3: Filter by GPA

GPA	# low	% low	# high	% high
A+	1	0.1%	636	75.9%
A	2	0.2%		
A-	42	5.0%	1	0.1%
B+	24	2.9%		
B	95	11.3%		
B-	263	31.4%		
C+	94	11.2%		
C	15	1.8%		
C-	101	12.1%		

of orders using a low of B- (46%) or B (33%). 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 X shows minimum and maximum thresholds used in SAT score filters and figure X shows thresholds for PSAT score. Although substantial overlap exists across university type, research universities tended to specify higher minimum score thresholds and higher maximum score threshoulds compared to ma/doctoral universities. In Figure X, for example, X% of orders by research universities specified a minimum SAT score of 1110 compared to X% of orders by ma/doctoral. X% of orders by research universities specified a maximum SAT score of 1310 or higher compared to X% 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.

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. 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.

Figure X shows orders by research universities that filtered on state, with separate maps for orders that filtered on out-of-state prospects and in-state prospects. CA, TX, and IL were the most commonly filtered states by universities searching for out-of-state prospects. 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].

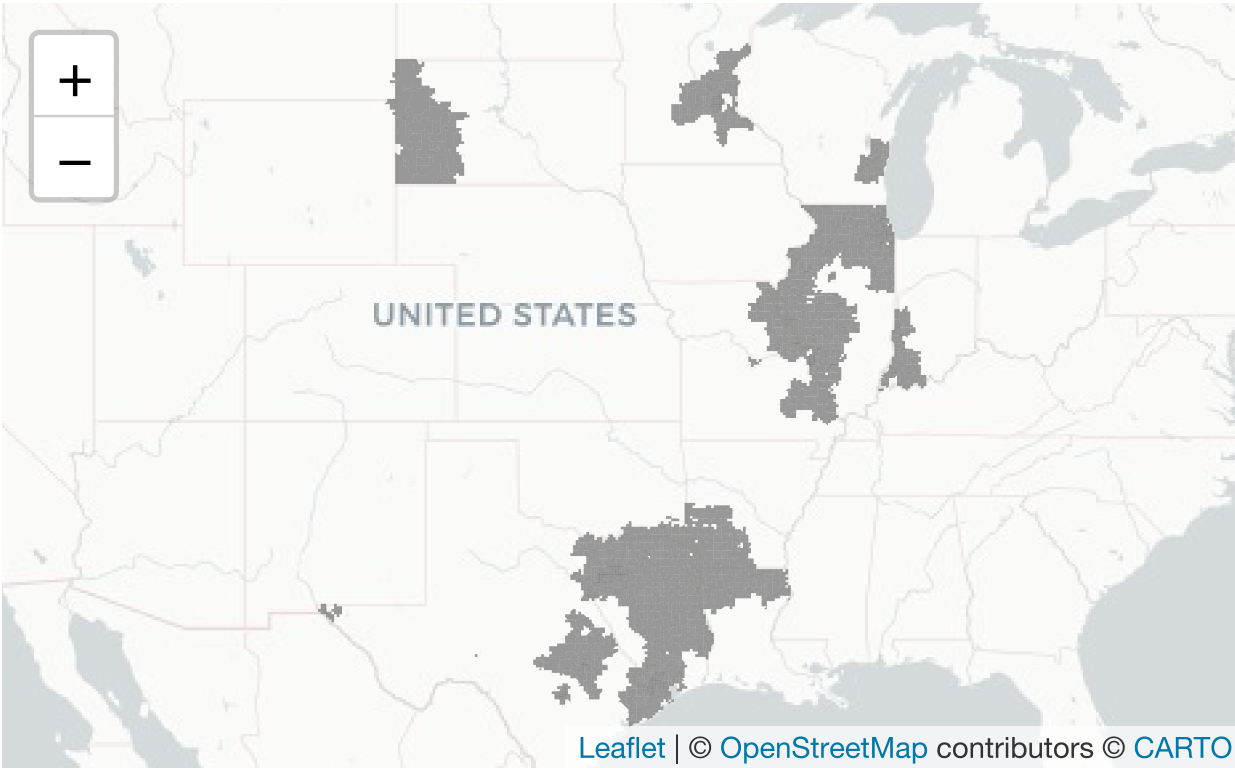
Segment filters come from the College Board’s “Segment Analysis Service,” which categorizes each high school and each neighborhood (census tract) into a type based on its demographic, geographic, academic, historical college-going characteristics (The College Board, 2011). Universities can then filter 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 and home zip code. 11% of orders by ma/doctoral universities filtered on state. These orders [ALWAYS?] were used to taget in-state prospects. 83% of orders by ma/doctoral universities filtered on home zip code, but orders by research universities did not filter in 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. XX of XX 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 X shows a map of three-digit zip codes filtered by a TX public university [OZAN SAYS INCLUDE]

In the second approach, universities specified a list of five-digit zip codes. Usually, five-digit zip codes were specified in a separate spreadsheet or text file that universities provided to College Board. XX (N=381) of XX orders that filtered on zip code filtered on five-digit zip codes. We know the five-digit zip-codes for XXX of these orders. [CAN WE SAY WHETHER

Figure 9: Filter by 3-digit zip code



THESE TENDED TO BE IN-STATE?]For the remaining XXX orders (n=157 orders), we were unable to obtain the zip-code file despite multiple requests.

One doctoral university gave us order summaries for XXX (?136?) student lists they purchased from College Board in in XXXX (?2019 and 2020). XXX of these orders specified five-digit zip codes. While we were unable to obtain the zip code 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 equality of opportunity 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.

Table 4: Filter by state

University state	Purchased state(s)	Count
AZ	Arizona	84
IL	IL	72
CA	Multi-state	52
CA	CA	41
AZ	CA	37
IL	Multi-state	26
TX	Multi-state	19
TX	TX	9
MN	Multi-state	3
CA	IL	1

4.1.4 Demographic Filters

Nearly all orders using demographic filters were made by research universities. Figure X 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 NativeHawaii/PI (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, and 10 orders filtering for Native American prospects (American Indian, Alaska Native, and/or Native Hawaiian or Other Pacific Islander) [CLEAN UP SENTENCE NOT ALL OF THESE GROUPS ARE NATIVE AMERICAN. AND NOT CLEAR WHETHER THESE ORDERS FILTERED FOR SPECIFIC GROUP OR FILTERED FOR EITHER].

Research universities also made 24 orders using gender filters. Across these orders, 75% filtered for women prospects and 25% filtered men prospects.

4.1.5 Combination of Filters

On average, the (N=XXX) orders in our dataset specified X.X critereia. Table 5 shows the ten most commonly used combinations of filters across orders by research (N=377) and ma/doctoral (N=458). [STATE SOMEWHERE THAT SOME FILTER IN THESE COMBINATIONS AREUSED AS **OR** CONDITIONS RATHER THAN **AND** CONDITIONS?].

Table 5: Filter combos used in order purchases

Filters	Count	Percent
grad_class,zip,sat,gpa	206	25%
grad_class,zip,psat,gpa	145	17%
grad_class,state,sat	67	8%
grad_class,state,psat	49	6%
grad_class,state,race,sat,psat,gpa,rank	39	5%
grad_class,state,sat,gpa	31	4%
grad_class,zip,sat,psat,gpa	28	3%
grad_class,sat,geomarket	26	3%
grad_class,psat,geomarket	23	3%
grad_class,state,race,psat,gpa	22	3%

For research universities, the top ten filter combinations account for 71% of all orders. The most common filter combination used included high school graduation class, state, and PSAT scores (n=47). These filters were also used across the top three combinations. For 41 [NUMBERS SEEM OFF IN PARAGRAH?] orders, high school graduation class, state, and PSAT scores were combined with race and gpa filters. Another 39 orders added race, gpa, SAT, and high school rank. The fourth and fifth most common combinations switched PSAT scores for 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 97% 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 investigates the student characteristics associated with particular combinations of filters.

4.2 RQ2: Characteristics of Prospects

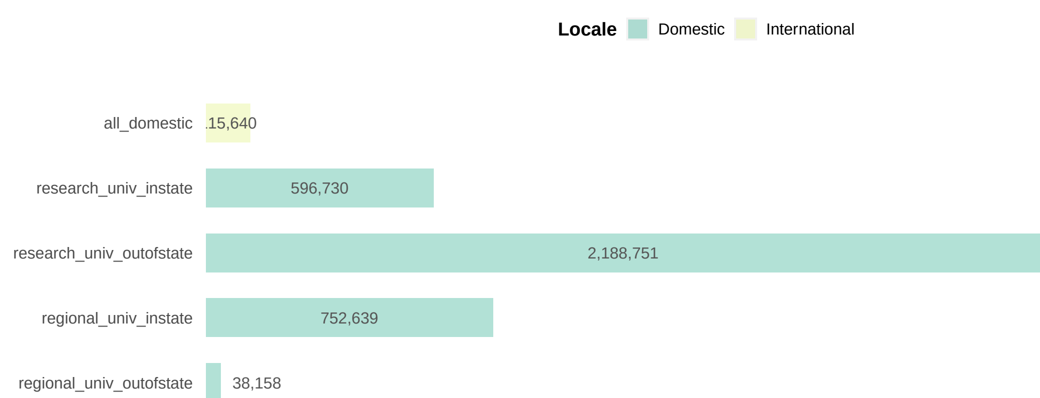
Research Question 2 asks, What are the characteristics of prospects included in student lists purchased by universities in our sample? Our analysis on the characteristics of prospects purchased by universities includes 598 orders resulting in 3,691,918 prospects. Figure 10 shows the total number of prospects 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 10 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" [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."

Figure 10: Number of prospects purchased



4.2.1 Public Research Universities

Figure 11 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 12 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 11: Prospects purchased by race

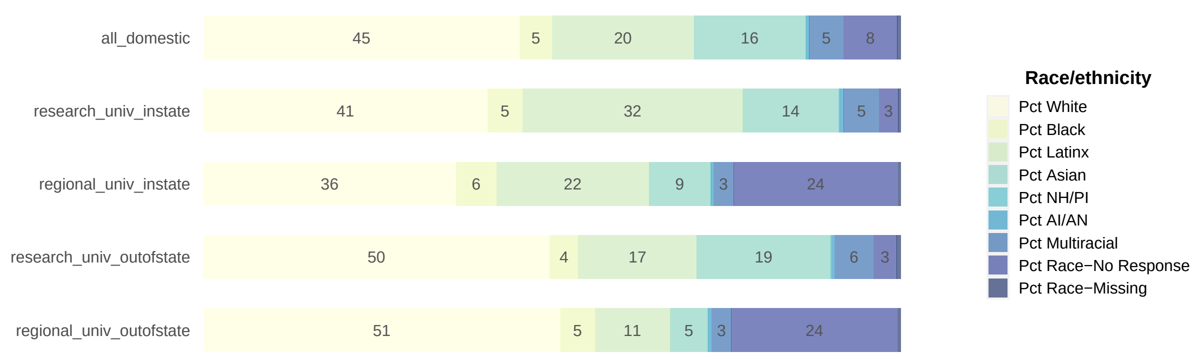


Figure X examines the extend to which in-state and out-of-state prospects purchased by research universities tend to reside in urban, suburban, or rural zip codes, as defined by the NCES/Census "locale" variable [CITE]. 34% of in-state prospects lived in urban areas and 39% lived in suburban areas. By 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 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 X, 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%).

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 11 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. [KARINA - CREATE TEXT FOR THIS PARAGRAPH ONCE WE FIGURE OUT DEAL W/ NO-RESPONSE FOR MA/DOCTORAL]

Figure 12 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 XXX. 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 XXX.

Figure 12: Prospects purchased by income

Figure XXX 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. 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 6 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.[5]

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 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.

[5] 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 6: Characteristics of prospects by filters

	All domestic	GPA	PSAT	SAT	HS rank	Race	Gender	Zip code	State	Segment	CBSA
Total N	3,576,278	1,129,129	1,833,369	971,237	971,237	306,209	39,546	165,924	1,200,141	186,519	146,313
Pct Race-No Response	8	3	3	3	3	2	3	4	3	3	3
Pct AI/AN	0	1	1	0	0	2	0	1	1	0	0
Pct Asian	16	15	17	15	15	9	38	13	18	27	28
Pct Black	5	7	4	7	7	10	1	8	5	3	2
Pct Latinx	20	23	19	22	22	43	6	27	24	11	8
Pct NH/PI	0	0	0	0	0	0	0	0	0	0	0
Pct White	45	45	50	47	47	27	47	43	43	51	53
Pct Multiracial	5	5	5	5	5	8	5	4	5	5	5
Median Household Income (mean)	93,505	91,746	95,007	92,251	92,251	85,047	110,587	87,861	92,184	113,165	117,222
Pct In-State	38	62	30	54	54	54	6	98	48	15	4
Pct Out-of-State	62	38	70	46	46	46	94	2	52	85	96
Pct Private	10	8	11	8	8	10	9	7	10	11	14
Pct Public	84	86	84	87	87	84	86	85	85	85	82
Pct School Unknown	5	5	5	5	5	6	4	9	5	3	4

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 6 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

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).

Figures 7 and 8, 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 XXXX and XXXX, 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

Table 7: 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 8: 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**

and maximum PSAT/SAT scores of 1450.[6] 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 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

7 and 8 show that selected neighborhood and high school clusters – highlighed 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 X 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 average median income – defined as XXX – of purchased prospects living in the metropolitan area compared to the median income of the metropolitan area.

For New York, Figure X shows White and Asian students comprised 56.5% and 26.5% of

[6] 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

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 XXXX – than the New York metropolitan area median income of XXXXXX.

Figure X 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 $148,371 compared to XXXXX 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.

4.3.5 Women in STEM

Two of the research universities in the study made orders targeting prospective students who are women interested in science, technology, engineering, and math (STEM). These orders targeted women interested in STEM primarily through two different filter patterns. The first pattern used SAT scores (ranging from 1300 to 1600), GPA (ranging from a low of B and high of A+), a state filter (in-state versus out-of-state), and students' self-reported intended major. The second pattern also used the same SAT, GPA, and state filters, but STEM interest was proxied via AP test scores. For in-state prospective students, orders filtered for prospects scoring from 3 to 5 on AP STEM tests. For out-of-state prospective students, orders filtered for prospects scoring 4 or 5 on AP STEM tests.[7]

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

[7] 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).

Figure 13: Metro area purchases by race

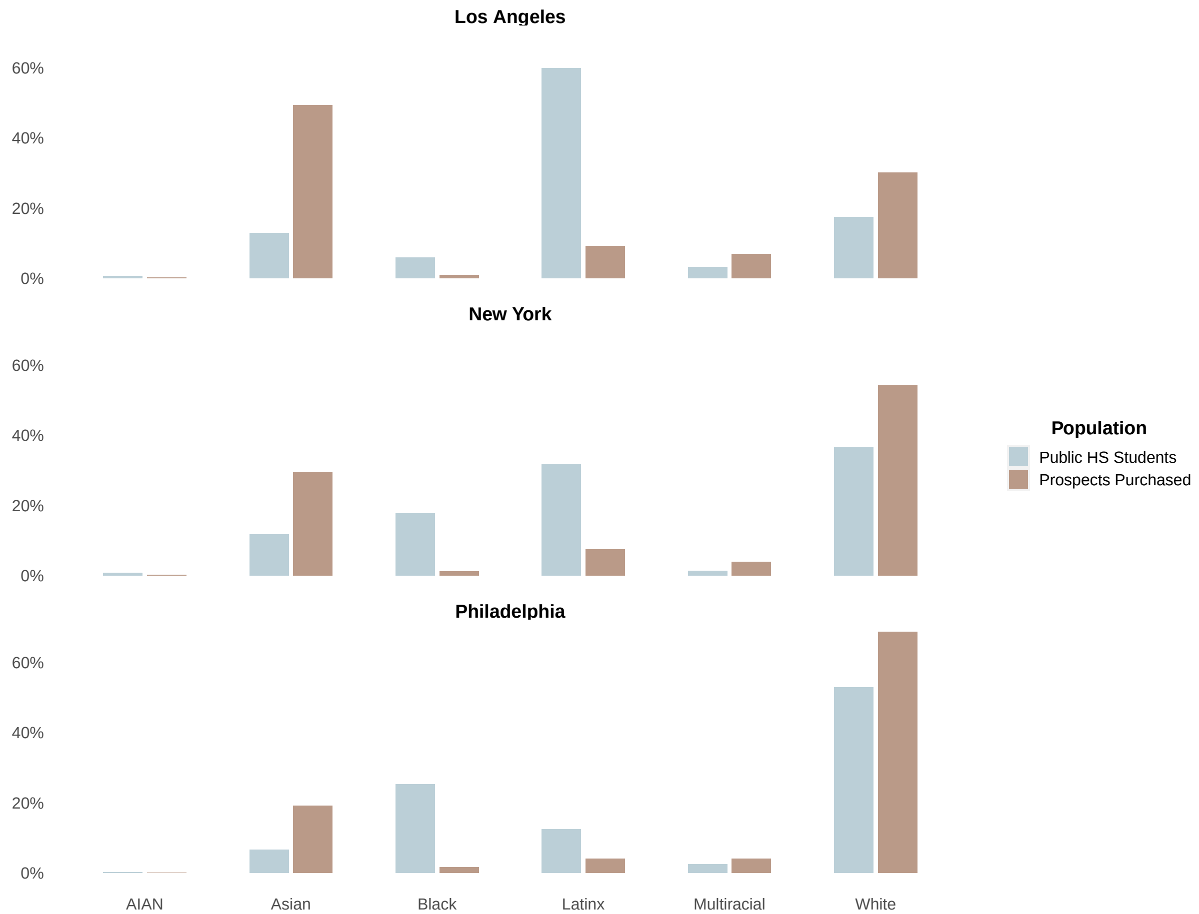
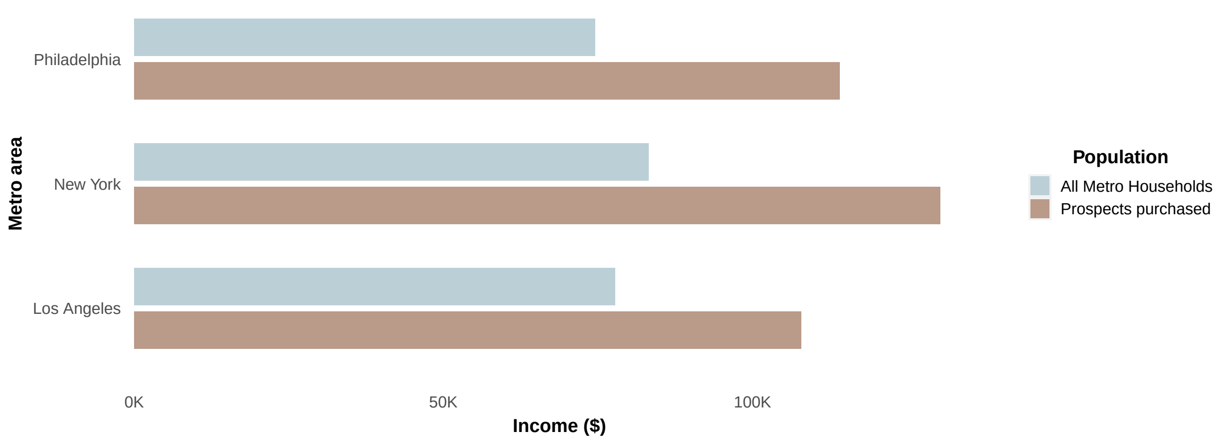


Figure 14: Metro area purchases by income



women interested in STEM, we analyze prospect profiles purchased in Texas. The University of California, San Diego made a total of 11 orders targeting women in STEM, which resulted in 12,938 prospect profiles purchased. Of the 10,668 total out-of-state prospective student profiles purchased by the university, 1,134 of these prospects are from Texas. We selected to "zoom" into Texas to take advantage of data provided by the Texas Education Agency on AP test takers as a comparison group for purchased prospects. Thus, we focus analyses on the 559 of the 1,134 Texas prospects whose profiles were purchased via AP filters. However, given the well-document racial and economic disparities in access to AP coursework, we first compare prospects to the population of 15-19 year olds in their home zip codes and in zip codes where zero prospective students' profiles were purchased. Broad patterns in the comparisons of prospects to the population of 15-19 year olds across zip codes were similar for the other two top ranked states with the most prospect profiles purchased via AP filters (e.g., New York, Florida) [DOUBLE CHECK THIS KS– TRUE FOR Metro areas but need to check entire states].

[KS: just realized comparison group race/ethnicity are not just women; includes all gender; need to pull ACS data with race/ethnicity BY gender; but I don't think general patterns will change significaly by include only women]

Our analysis first focuses on comparing the racial characteristics of Texas prospects whose profiles were purchased to the population of 15-19 year olds in their home zip codes. The university purchased at least one prospective students' profile from 203 of the 1,935 zip codes in Texas. Figure X presents the racial characteristics of prospects to the population of 15-19 year olds in these 203 zip codes. The figure shows two general trends consistent across orders targeting Women in STEM. First, White and Asian prospects are overrepresented relative to the population of 15-19 year olds in their home zip codes. For example, nearly 40% of all purchased prospects are White while 38% of the 15-19 year olds in their home zip codes are also White. This difference is much larger for Asian prospects, who make up nearly 30% of all purchased prospect profiles but only make up about 6% of the population of 15-19 year olds in their home zip codes. Second, Black and Latinx prospects are underrepresented to their zip code populations. Black and Latinx prospects make up 2% and 20% of all purchased prospects, respectively, while their home zip code's population of 15-19 year olds are on average 10% Black and 36% Latinx. It's important to note that only 3 of the 559 prospects purchased across Texas were Native American. While looking at proportions across the population of 15-19 year olds in zip codes invisibilizes the number of Native American students in relation to other racial/ethnic groups, the 3 prospects are relative to a total of 3,623 Native American 15-19 year olds living in these 203 zip codes.

Figure 15: FIGURE COULD BE SOME VARIATION OF THESE DATA

As a proxy for comparing prospects to prospective students in Texas whose profiles were not purchased by the university, we also compare the racial and economic characteristics of prospects to the population of 15-19 year olds in the 1,732 non purchased zips in Figure X. Comparing prospects to the average population of zip codes where zero prospective students' profiles were purchased, Asian prospects are again overrepresentated while White prospects shift to being slightly underrepresented. For example, on average, less than 2% of 15-19 year olds in non-purchased zips are Asian but nearly 30% of prospects are Asian. The population of Black and Latinx 15-19 year olds are relatively the same in non-purchased zips to prospects' home zip codes, which result in similar disparities between prospects and non-purchased zip code populations to comparisons with their home-zip codes above.

Figure X also shows the economic characteristics of prospects and prospective students in Texas whose profiles were not purchased by comparing the average median household income of prospects' home zip codes to the the average median household in the 1,732 non purchased zip codes. Prospects whose profiles were purchased by the university tended to be much more affluent than non-purchased prospetive students. For example, purchased prospects live in Texas zip codes where the average median household income is $84,722. In comparison, populations living in the 1,732 non purchased zips have an average median income of $56862.

Lastly, we use AP participation data from the Texas Education Agency to compare the racial characteristics of prospects whose profiles were purchased by the university to the population of AP science test takers in Texas.[8] The racial and economic inequities in access to AP coursework and disparities in passing rates are well-documented (CITE). However, we compare prospects to test takers to illustrate how using AP score range filters, rather than just proxying STEM interest by students with have the ability to and take AP science coursework, further exacerbates inequities in whose profiles are purchased.

Figure X compares the racial characteristics of prospects to AP science test takers in Texas. Even though AP test takers is likely to inequitably underpredict the number of women interested in STEM due disparities in access to advanced coursework, we still see large disparities between prospects and test takers. For example, Black students make up 6% of AP science test takers but only 2% of purchased prospects. Similarly, Latinx students make up 40% of test takers but only 15% of AP test takers.

Figure 16: FIGURE COULD BE SOME VARIATION OF THESE DATA

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

[8]These figures also include students who took the International Baccalaureate science exam

were utilized almost exclusively by research universities. As shown in Figure X, 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). Filtering on race/ethnicity when purchasing student list may be a means of promoting racial diversity in college access, particularly given the trend away from race-conscious admissions policies.

However, drawing from critical legal scholarship, Jaquette, Salazar, & Martin (2022) suggest that student list purchases that filter for underrepresented ethnic or racial groups may simultaneously utilize filters that tend to exclude students from predominantly non-white communities:

> Drawing from the theory of racial capitalism (Leong, 2013), we argue that race/ethnicity filters tend to privilege whiteness, even when used to target non-white prospects. Leong (2013) builds on Harris (1993). Whereas "nonwhiteness" was historically "used as a basis for withholding value by denying nonwhite people legal rights and privileges" (Leong, 2013, p. 2155), nonwhiteness now confers social and legal value as a function with society's preoccupation with diversity. The commodification of nonwhiteness – a "commodity to be pursued, captured, possessed, and used" (p. 2155) – encourages organizations to prioritize representational diversity, which Harris (1993) argues is exemplified by universities enrolling and marketing a diverse student body as a marker of status and prestige. However, selective universities pursue representational diversity while simultaneously privileging characteristics associated with whiteness (e.g., a "good high school", "interesting extracurricular activities", "good scores") (Jack, 2019; Stevens, 2007; Thornhill, 2019). By combining race/ethnicity filters with academic achievement (e.g., AP test score range), geographic, and/or geodemographic filters, universities can screen for Students of Color who have characteristics associated with whiteness, often as a function of attending a predominantly white high school.

Figures X and X present results 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, predonominantly 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 X 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, allocates each student to one race/ethnicity category. 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. [A COUPLE OF SENTENCES SUMMARIZING RESULTS]

Figure X describes the high schools these prospects attended. The left column examines attendance at public and private schools. Across the New York CBSA, X% percent of high school students attended a private high school compared to X% of purchased prospects. The middle column examines household income. The prospects purchased from New York lived in zip codes where the average income was $107,829, considerably higher than median income of XXXX in the New York CBSA. New York public high schools with at least one purchased prospect were located in zip codes where the average household income was $109,695, which was considerably higher than that of public high schools where no prospects were purchased. The right column examines race/ethnicity. Public high schools where no prospects were purchased were, on average, 30.2% Black, 41.4% Latinx, 19.3% white, and 6.92% Asian, where as schools with at least one purchased prospects were on average, 10% Black, 20.8% Latinx, 54.9% white, and 12.3% Asian.

Results for Miami differed from New York. The differences in household income were less pronounced than the case of New York. 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 (6.9% of total enrollment) but a large number of Latinx students (37.4% of total enrollment). Results for Houston show that purchased prospects also tended to live in relatively affluent communities. However, most purchased prospects (84.8%) attended public schools and public schools with at least one purchased prospect tended enrolled 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 high schools seems to differ by metropolitan area, depending on local patterns of school segregation. In New York – and also Philidelphia and Chicago (results not shown) – purchased Black and Latinx prospects 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 – purchased Black and Latinx prospects 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.

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