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

Karina Salazar Ozan Jaquette Crystal Han

1 Executive Summary

Universities identify prospective undergraduate students by purchasing "student lists" from College Board, ACT, and other vendors. Student lists contain the contact information of prospects who satisfy "search filter" criteria (e.g., test score range, high school GPA, zip code) specified by the university, who can then be recruited via mail, email, or targeted social media.

Recent research suggests that student lists have surprisingly large effects on college access outcomes for millions of students each year. The College Board Student Search Service product allows accredited institutions to "license" the contact information of test-takers. Howell, Hurwitz, Mabel, & Smith (2021) compared SAT test-takers who opted in versus out of Student Search Service, controlling for variables like SAT score and parental education. Based on this study, College Board states that "students who connect with colleges through Student Search are 25% more likely to enroll in 4-year colleges . . . [and] 31% more likely to graduate in 4 years than similar students who weren't identified through Student Search" (College Board, 2022c). Furthermore, "these enrollment and completion benefits associated with Search are as large or larger for Black, Hispanic, and first-generation students" (College Board, 2021a).

Whereas Howell et al. (2021) examine the outcomes of test-takers who opt in versus out of Search, we examine the search filters universities specify when buying lists and the characteristics of prospects whose contact information (i.e., profiles) were purchased. Following two years of data collection, analysis, and investigation into the student list business, the thesis that emerges from our findings is that student list products are structurally racist and classist.

Structural racism is “a form of systematic racial bias embedded in the ‘normal’ functions of laws and social relations” (Tiako, South, & Ray, 2021, p. 1143), whereby processes viewed as normal or neutral systematically advantage dominant groups and disadvantage marginalized groups. Organizations and organizational processes are fundamental mechanisms of structural racism (Ray, 2019). University recruiting behavior exemplifies this claim. On one hand, “predatory” for-profit colleges practice reverse-redlining (Cottom, 2017). On the other, selective universities systematically target affluent, predominantly white schools and communities in off-campus recruiting visits (Jaquette, Han, & Castaneda, forthcoming; Salazar, 2022). We began the student list project to investigate the presence of structural racism in the list-buying behaviors of universities. However, Noble (2018) shows that products based on algorithms are another source of structural racism. Over time, we came to the conclusion that the student list products themselves may be structurally racist (and classist). In turn, these products structure the recruiting behavior of colleges and universities.

The student list project. This report as part of a broader project on the student list business, which resulted in three reports. First, Jaquette et al. (2022) describe the market for student list data and how the market is changing as a result of technological advances, entry by for-profit interests, and the test-optional movement. Second, this report analyzes student lists purchased from College Board. Third, Jaquette & Salazar (2022) discuss regulations and policy solutions.

We collected data by issuing public records requests to all public universities in CA, IL, MN, and TX. Data collection focused on the three largest student list vendors. For each list purchased for the purpose of undergraduate recruiting from 2016 through 2020, we requested two related pieces of data: (1) the order summary, which shows the search criteria specified for the student list purchase; and (2) the de-identified prospect-level list produced from these criteria. This report focuses on student lists purchased from College board and addresses three research questions:

1. Which filter criteria (e.g., high school graduating class, SAT score range) 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 prospects included in purchased student lists?

We analyze student lists purchased by 14 public universities, including 7 public research universities and 7 ma/doctoral universities. We obtained 830 student list orders, which is the analysis sample for RQ1. We obtained de-identified student list data about 3,663,257 prospects, which is the analysis sample for RQ2. We received both the order summary data and the de-identified student list data for 414 orders associated with 2,549,085 prospects, resulting in the analysis sample for RQ3.

RQ1. The search filters utilized by universities in our sample can be categorized into four bins: academic (e.g., high school GPA); geographic (e.g., state, zip code); demographic (e.g., gender); and student preferences (e.g., intended major). At minimum, most orders specified high school graduating class, one or more academic achievement filters and one or more geographic filters.

Compared to ma/doctoral universities, the research universities in our sample tended to set higher thresholds on academic achievement criteria, were more likely to utilize demographic filters, and they utilized a broader range of geographic filters (e.g., state, geodemographic "segment," "geomarket," metropolitan area) as means of targeting out-of-state prospects.

RQ2. We examined the characteristics of prospects whose profiles were purchased on the dimensions of ethnicity/race, household income, and geographic "locale" (e.g., urban, suburban, rural). Public research universities in our sample purchased student lists with more out-of-state prospects than in-state prospects. Compared to in-state prospects, out-of-state prospects were more affluent, more likely to identify as white or Asian, and more likely to live in suburban areas. Ma/doctoral universities in our sample primarily purchased lists with in-state prospects and these in-state prospects were slightly less affluent than those in student lists purchased by research universities.

RQ3. The most important analyses of the report investigate the relationship between search filter criteria and the characteristics of prospects whose profiles were purchased. In contrast to RQ1 and RQ2, RQ3 faces fewer external validity concerns because a particular combination of search criteria yields the same set of prospects regardless of which university placed the order.[1] Analyses for RQ3 focus on four "deep dives" of commonly observed or thematically important search filter patterns: geodemographic segment; zip code; women in STEM; and targeting URM students.

Geodemographic segment. The College Board Segment Analysis Service (herein Segment) is an add-on set of filters that enables universities to filter prospects by the "type" of neighborhood they live in and the "type" of high school they attend. Geodemography is a branch of market research that estimates the behavior of consumers based on where they live.

[1] One caveat to this statement is that most student list products enable universities to exclude prospects that were included in a previous order.

The College Board (2011b) white paper on Segment illustrates that geodemography is based on problematic assumptions about segregation:

> The basic tenet of geodemography is that people with similar cultural backgrounds, means, and perspectives naturally gravitate toward one another or form relatively homogeneous communities; in other words, birds of a feather flock together (p. 1).

Segment categorizes every U.S. census tract into one of 33 "educational neighborhood clusters" (EN:51-EN:83) and categorizes every U.S. high school into one of 29 "high school clusters" (HS:51-HS:79) based on socioeconomic, demographic, and education characteristics, including historical college-going behavior. A Segment customer may, for example, purchase the profiles of prospects who scored between 1100-1300 on the SAT and attend a high school in cluster HS:63. Unfortunately, Segment neighborhood and high school clusters are highly correlated with race and income.

We analyzed eight orders by a public research university that utilized the same set of Segment filters and specified very similar academic criteria across orders. These Segment orders – resulting in 131,562 prospects whose profiles were purchased – yielded problematic socioeconomic and racial patterns. For example, 9,126 prospects' profiles were purchased from the Philadelphia metropolitan area. These prospects lived in zip codes where the average household income was $136,000, much higher than the metro average of $84,000. The racial composition of prospects whose profiles were purchased was 71% white, 18% Asian, 2% Black, and 5% Latinx. By contrast, the racial composition of public high schools in the Philadelphia metro was 44% white, 5% Asian, 35% Black, and 13% Latinx.

Zip code. Most student list products allow universities to filter prospects by zip code. We analyzed the racial composition of prospects that would result from a student list purchase that filtered on affluent zip codes. This analysis was based on four student lists that targeted California high school students – each filtering for a different SAT/PSAT test score range – by a public research university. Next we restricted analyses to prospects living in the Los Angeles metro area. Finally, we compared prospects living in a zip code in the top income decile – our hypothetical zip code filter – to prospects living in a zip code in the bottom nine income deciles.

Results show that filtering for affluent zip-codes leads to substantial declines in the racial diversity of prospects. This is true across several score ranges (low, medium, high). For example, for prospects with "medium" PSAT scores of 1190-1260, prospects living in a top income decile zip code were 51% white, 23% Asian, and 15% Latinx. By contrast, prospects living in the bottom 9 deciles were 29% white, 36% Asian, and 26% Latinx. Thus, the hypothetical decision to filter on affluent zip codes results in a higher share of white prospects being recruited.

***Women in STEM* and *targeting URM*.** Our final two deep-dives, respectively, analyse purchases that target women in STEM and purchases that target underrepresented Students of Color. Orders that targeted women in STEM – based on AP scores (4+) or based on the combination of SAT scores (1300+) and intended major – yielded lists that largely consisted of affluent, white and Asian prospects. Orders that filtered for underrepresented students of color with relatively high SAT scores (1200-1380) tended to target prospects from wealthy communities. Depending on local patterns of school segregation, these purchases disproportionately excluded Students of Color attending predominantly non-white high schools.

Discussion. Over time, College Board Student Search Service added search filters to identify underrepresented student populations (e.g., low-income students, rural students, National Recognition Programs). In our data collection, we observed many instances of universities utilizing features of the Student Search Service toward this end. For example, one university purchased all profiles in the U.S. for prospects who identify as American Indian/Alaska Native and scored between 1040-1600 on the SAT. Another university made 58 purchases – yielding 53,784 prospects – targeted students with family income below $45,000. Thus, we acknowledge that the Student Search Service product can be to increase equity in educational opportunity. Nevertheless, Student Search Service can – intentionally or unintentionally – easily be used in ways that harm opportunities for underrepresented student populations. Products that have a high likelihood of causing harm must be regulated.

We believe that College Board student list products are structurally racist because filters viewed as "normal" systematically benefit dominant groups and exclude underrepresented groups.

Geographic search filters enable universities to target prospects who live in particular places. Residential segregation is a product of systemic racism. Products that target prospects based on where they live, without considering the history of racial segregation, perpetuate the racial segregation in access to educational opportunity. Zip codes are highly correlated with race and income. From an equality of educational opportunity perspective, what is the rationale for a product that enables universities to target students living in one zip code and exclude students living in the neighboring zip code?

Geodemographic filters are even more problematic. They target more precise geographies (e.g., census tract, high school) than zip code. They enable universities to target students from the "right" kind of neighborhood or school, without explicitly naming them. Rather than targeting prospects based on their educational achievement and aspirations, geodemographic filters enable universities to target prospects based on the past college-going behavior of their peers.

College Board student list products are fundamentally based on standardized tests (SAT, PSAT, AP). Rates of test-taking differ across race and class, yielding systematic inequality in who is included in the underlying database and, in turn, who is recruited by universities. The test-optional movement may exacerbate inequalities in test-taking. Moreover, College Board – and ACT – search filters encourage universities to filter prospects by test score, but decades of research finds that college entrance exams exhibit both racial and socioeconomic bias (Freedle, 2003; Santelices & Wilson, 2010).

Over the past decade, College Board – and ACT – have added new search filters (e.g., "Interest In My Peers," "Environmental Attributes") that facilitate micro-targeting of the "right" kind of students. Ironically, the primary reason universities value these filters is because the price of names is so high. In 2021, College Board charged $0.50 per name. In 2022, they are transitioning to a tiered subscription model. College Board uses revenues from "these license fees to help support its mission-driven work" (College Board, 2022b).

College Board describes itself as a "mission-driven not-for-profit organization that connects students to college success and opportunity . . . , founded . . . to expand access to higher education" (College Board, 2022a). The College Board Student Search Service is literally central to this stated mission, not a money-making side-hustle. If College Board is serious about their mission, they should eliminate problematic micro-targeting search filters and provide all names for free.

2 Introduction

In March 2020, a selective public research university purchased 45 "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.

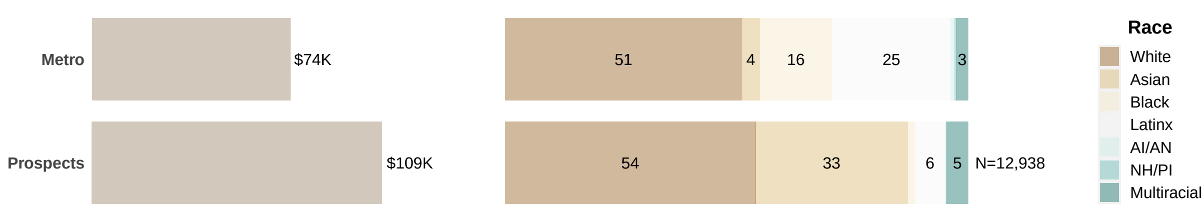
Several of the student lists purchased by the university targeted women in STEM fields. For example, an order the university named "NR 2021 Female AP STEM" targeted nonresident high school students from 26 states, who identified as women, were in the high school class of

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. However, analyses of the prospects whose profiles were purchased via "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 profiles were purchased across 11 total orders made by the university targeting women in STEM.[2] These prospects live in zip codes where the average median household income is $109,000, compared to $74,000, which is the average median household income of all zip codes in the 27 states the prospects came from.[3] Figure 1 also shows very few prospects whose information were purchased are Latinx (6%), Black (2%), Multiracial (5%), or Native American students (0.2%); whereas White (54%) and Asian (33%) students make up more than 8 of every 10 women in STEM prospects. This is compared to the racial composition of all female 12th graders in public high schools in the purchased 27 states, where Latinx (25%) and Black (16%) students make up more of the enrolled population and Asian (4%) students make up much less.

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



Note: Public high schools that satisfied the following criteria were included: enrolls at least ten female 12th graders; is a non-virtual school; is an open, new, or reopened school. Prospects whose race were unknown (0.9%) or did not report their race (3%) were excluded.

[2] Three of the 11 orders resulted in 0 profiles purchased. Students from the remaining orders came from 27 unique states.

[3] Zip code-level income data for homeowners between 25-64 years old is used. This was calculated by taking the average of the median income for age group 25-44 and age group 45-64 years olds, as reported in the 2019 American Community Survey (ACS) 5-year estimates. However, disaggregated income data is not available for all zip codes, so zip codes with missing data do not appear in our results.

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 (Allison Socol & Ivy Morgan, 2020; Gagnon & Mattingly, 2016; Genevieve Siegel-Hawley, 2021; Jesus Cisneros & Corley, 2014; Sponsler, Wyatt, Welch, & Mann, 2017; Theokas, 2013) and SAT/PSAT test-taking (Cook & Turner, 2019).[4]

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 recruited 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 prospects whose profiles are purchased, 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 et al., 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?
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 prospects included in purchased student lists?

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

[4] Although, some student list vendors have acquired sources of student list data beyond test-takers. ACT achieved this by acquiring NRCCUA in 2018. Years earlier, NRCCUA replaced the paper surveys students filled out during school with an online college search engine named myOptions. See Jaquette et al. (2022) for more details.

and future research.

3 Background

This section situates student lists within the admissions recruiting process. We describe how universities buy lists and what information they contain. We focus on lists 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.

3.1 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 (or "profiles") has been purchased. "Inquiries" are prospects that contact your institution and consist of two types: first, inquiries who respond to an initial solicitation (e.g., email) from the university; and second, "student as first contact" inquiries who reach out to the university on their own (e.g., 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 (e.g., DesJardins, Ahlburg, & McCall, 2006; Ehrenberg & Sherman, 1984; Epple, Romano, & Sieg, 2006).

Figure 2: 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.

3.2 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, 2022b) to "license" their contact information. In fall 2021, College Board charged $0.50 per name (College Board, 2021b).

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, race, 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), which make up each prospect's "profile". The template for a College Board student list can be found here.

3.3 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 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. Moore (2017) provides a similar analysis of ACT's Educational Opportunity Service (EOS). Figure 3 reproduces the main results of Howell et al. (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.[5]

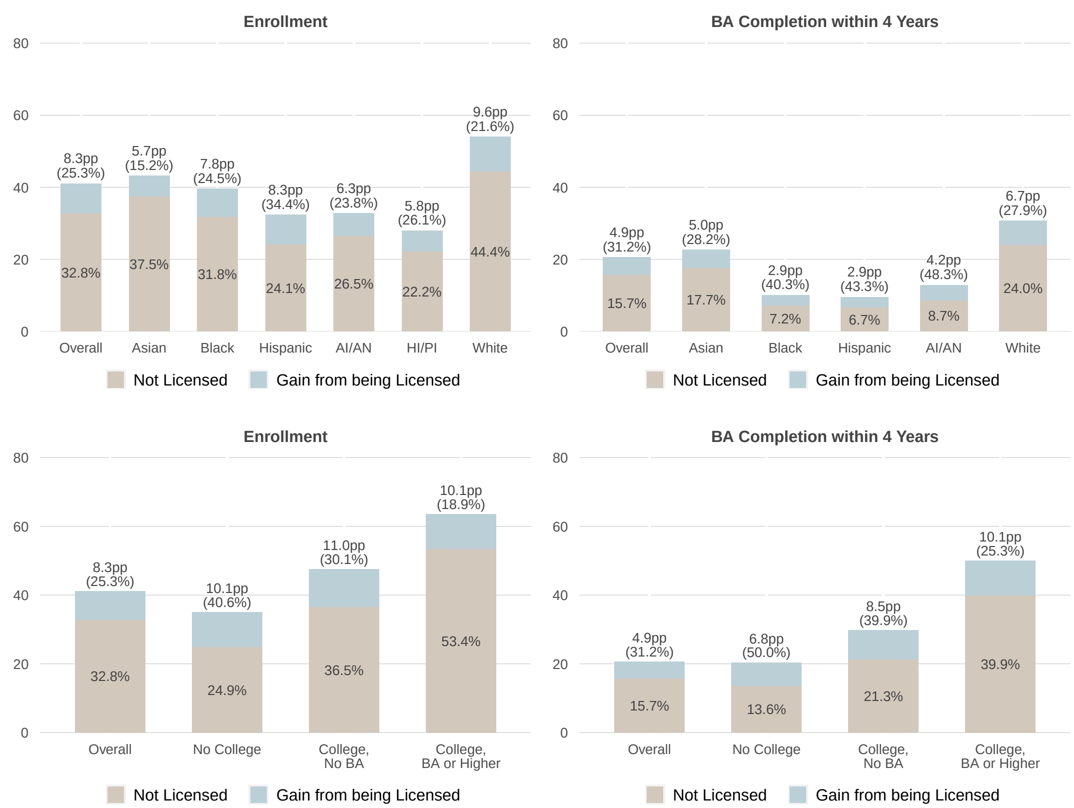
Figure 3 shows that participating in Search was associated with a larger percent change in the relative probability of attending a 4-year institution for students who identified as Black (24.5%), Latinx (34.4%), American Indian or Alaska Native (23.8%), and Native Hawaiian or Pacific Islander (26.1%) 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

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

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 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: Student Search Service and college enrollment and degree completion



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.*

4 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.

4.1 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.[6]

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.[7]

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 A1 shows an example of a College Board order summary. In Figure A1, the university purchased the contact information of 2020 high school graduating class prospects living across 10 different states (Colorado, Illinois, New York, Connecticut, Washington, Virginia, Maryland, California, Massachusetts, and New Jersey), that scored between 1470 and 1520 on the PSAT, and a high school GPA ranging from B- to A+. With respect to de-identified prospect-level lists, this link shows partial data from the student list associated with this

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

[7] ACT acquired NRCCUA in 2018. Years earlier, NRCCUA replaced the paper surveys students filled out during school with an online college search engine named myOptions. The ACT Encoura platform incorporates student list data derived from ACT assessments and data derived from the myOptions search engine. For full details see Jaquette et al. (2022)

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).

Records that public universities provided in response to our public records requests become public records. Nevertheless, this report does not name individual universities in order to focus attention on student list products rather than the behavior of individual universities.

Data collection sample. The broader research project sought data about student list purchases – from College Board, ACT, and NRCCUA – from all public universities in IL, MN, CA, and TX. However, this report analyzes student lists purchased from College Board. We exclude student list purchases by MN public universities from this report because Minnesota is predominantly an "ACT state" and the majority of MN (regional) public universities primarily purchased lists from ACT rather than College Board.

Thus, for the purpose of this report, the data collection sample consists of all public universities in IL, CA, and TX. Additionally, we collected data from two universities in an unnamed western state because a law firm was willing to represent our data collection efforts in this state.

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 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. Appendix Figures A2 and A3, respectively, describe the Carnegie Classification and and geographic location of public universities in our data collection sample (excluding the unnamed western state). Most are master's or doctoral universities and located in urban areas.

Data collection process. Collecting quantitative data via public records requests is a painstaking process. Initially, the majority of universities denied our requests or did not respond. We later obtained pro bono representation from four law firms, which substantially increased the success of data collection. However, we were unable to obtain representation for Texas.

Even with law firm representation, data collection remained difficult. Some universities provided records that were not usable for quantitative analyses (e.g., summary statistics

Table 1: Summary of data received

State	# received order summary	# no order summary	# received list	# no list	# received both	# did not receive both
CA	9	23	13	19	9	23
IL	9	3	9	3	8	4
TX	15	20	16	19	10	25

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). We learned that many universities outsourced student list purchases to a third-party consulting firm. Unfortunately, we were rarely able to obtain usable data from these universities. A small number of universities denied requests based on potentially questionable legal rationale, but we lacked the resources to litigate.

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. The results presented below are based on data received from universities that provided usable order summary data and usable student list data.

4.2 Research Design

Analysis sample. Table 2 summarizes the number of order summaries received and the number of prospects whose profiles were purchased across the sample of universities.

- We received order summaries for 830 student list purchases. These 830 are the analysis sample for RQ1, which is about the filter criteria specified in student list purchases.
  - However, we did not receive the de-identified student list data for 416 of these orders
- We received de-identified prospect-level data for 3,663,257 prospects from 594 orders. These 3,663,257 prospects are the analysis sample for RQ2, which is about the characteristics of prospects whose profiles were purchased.
  - However, we did not receive the order summary data for 1,114,172 of these prospects
- We received both the order summary data and the de-identified student list data for 414 orders associated with 2,549,085 prospects, resulting in the analysis sample for RQ3, which is about the relationship between student list filter criteria and the characteristics of prospects whose profiles were purchased.

Research design and research questions. Decisions about research design and research questions were informed by both data limitations and substantive considerations. A large-N statistical design is not appropriate because we received order summary data and student

Table 2: Summary of orders and prospects

RQ1	RQ3	RQ2	RQ3
# orders total	**# orders with list**	**# prospects total**	**# prospects with order**
830	414	3,663,257	2,549,085

list data from a non-random sample of universities. We can conceive of our analysis as a multiple case study research design (Eisenhardt, 1989) in which 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, we prefer that analyses focus on student list products rather than the behavior of universities (customers) who buy the product. Our rationale is that inequality in purchased versus excluded prospect profiles is substantially a function of (A) which prospective students are included in the underlying data base and (B) the set of filters the product allows universities to utilize. 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:

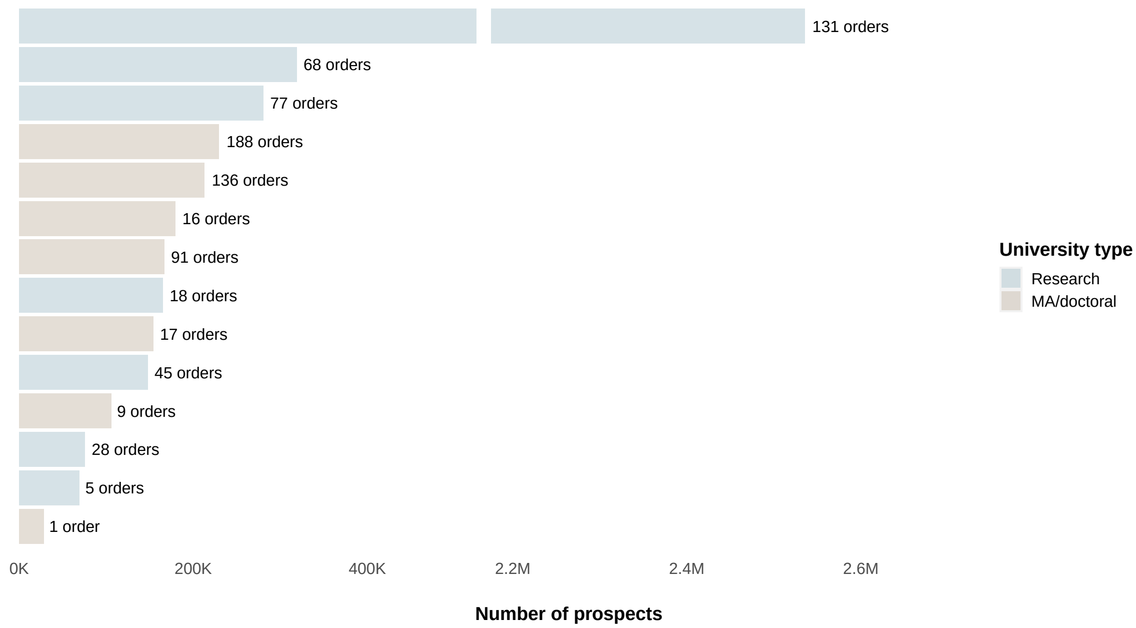
1. Which filter criteria were selected in student lists purchased by universities in our sample?
2. What are the characteristics of prospects included in student lists purchased by universities in our sample?
3. What is the relationship between student list filter criteria and the characteristics of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

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.

Figure 4 presents the 830 total orders – purchased by 14 universities – by university type and the total number of prospects whose profiles were purchased. The seven master's universities purchased 458 lists, while the seven research universities made 372 orders. The number of total prospects whose profiles were purchased within each order varied widely. Across all 830 orders, the median number of prospect profiles purchased per order was 998, whereas the mean was 5,626 (sd=17,726). Despite making fewer total orders than master's universities, research universities on average purchased more than quadruple the number of students' profiles per order (9,659 versus 2,351). Results are strongly influenced by universities that made a large number of orders (RQ1) and purchased a large number of prospects' profiles (RQ2). In particular, one public research university made 131 orders and purchased 1568355 prospects' profiles. Appendix Figures **??** and Figure **??**, respectively, show the number of student lists purchased and the number of prospects' profiles purchased by Carnegie Classification and state.

Figure 4 presents the 830 total orders – purchased by 14 universities – by university type and the total number of prospects whose profiles were purchased. The seven master's universities purchased 458 lists, while the seven research universities made 372 orders. The number of total prospects whose profiles were purchased within each order varied widely. Across all 830 orders, the median number of prospects whose profiles were purchased per order was 998, whereas the mean was 5,626 (sd=17,726). Despite making fewer total orders than master's universities, research universities on average purchased more than quadruple the number of prospect profiles per order (9,659 versus 2,351). Results are strongly influenced by universities that made a large number of orders (RQ1) and purchased a large number of prospects' profiles (RQ2). In particular, one public research university made 131 orders and purchased 1,568,355 prospects' profiles. Appendix Figures A4 and Figure A5, respectively, show the number of student lists purchased and the number of prospects' profiles purchased by Carnegie Classification and state. »»»> Stashed changes

Figure 4: Orders and prospects purchased by research vs. ma/doctoral



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. We also 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 RQ3, we contextualize the characteristics of prospects whose profiles were purchased by showing the characteristics of one or more comparison groups (e.g., all high school graduates in the metropolitan area).

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. 2017-18 data for IPEDS, CCD, and PSS data were used. The Census American Community Survey (ACS) provide data about community characteristics. We use zip-code and metro level data from ACS 2015-19 5-year estimates.

5 Results

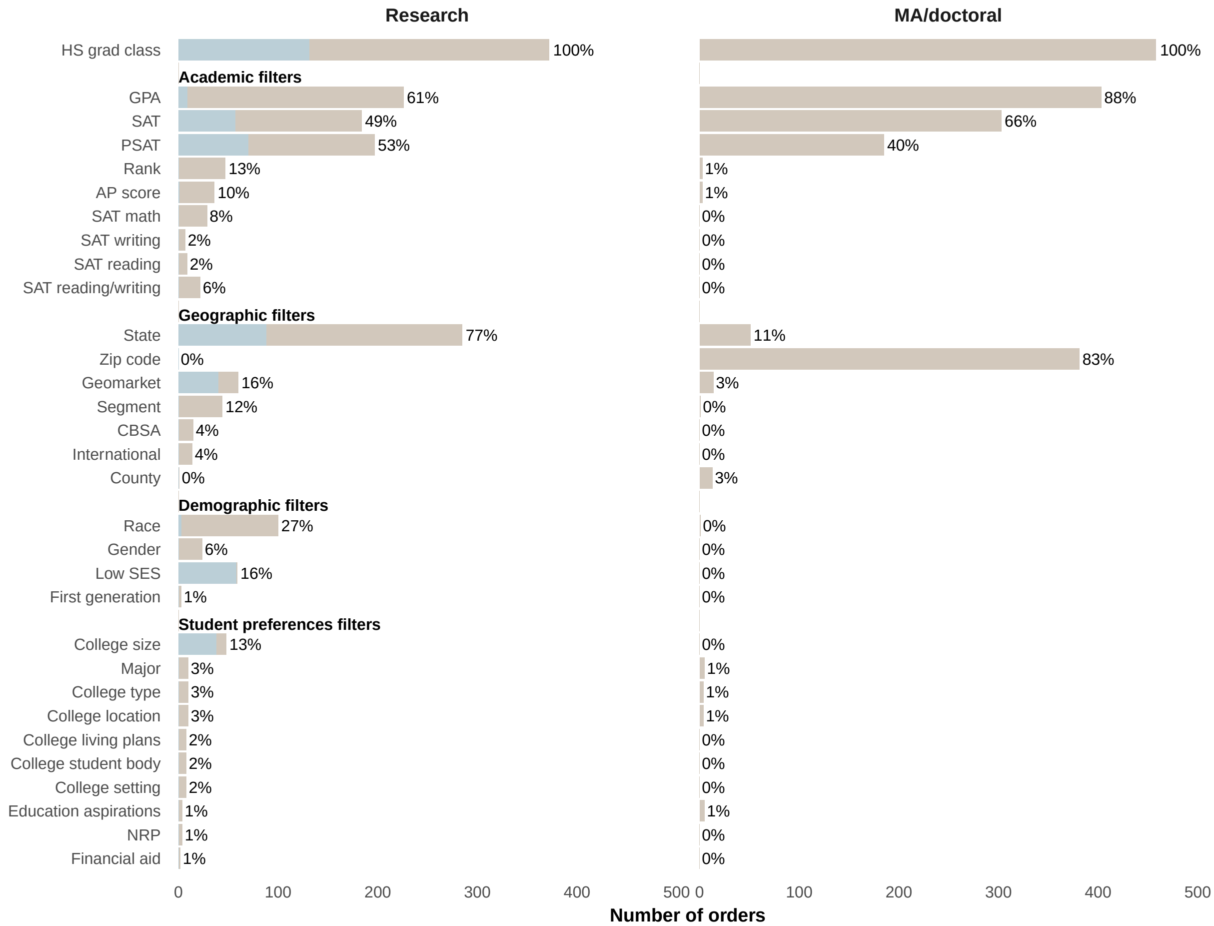
5.1 RQ1: Filter Criteria Selected in Purchases

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 four groups: academic (e.g., GPA, PSAT, SAT, academic rank, AP Score); geographic (e.g., zip code, state, segment, core based statistical area, geomarket, international); demographic (e.g., race/ethnicity, gender); and 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.

5.1.1 Broad Patterns

Figure 5 shows how often filters were used by university type. While student list purchases typically filter on multiple criteria, Figure 5 illustrates the prevalence of each individual filters. All orders by both research universities (n = 372) and ma/doctoral universities (n = 458) filtered by high school graduation class.

Figure 5: Filters used in order purchases by research vs. ma/doctoral



Note: One research university placed a large amount of orders, which influenced the overall filters used for all research universities. The contribution of this particular university is shown using a different color in the figure above.

Academic. 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.

Geographic. 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, but 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 these filters.

Demographic. 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 were 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 (0.8%), and financial-aid need (0.5%).

Student preferences. Lastly, filters for student preferences were utilized less often than academic, geographic, and demographic filters. These filters were utilized by research universities and generally not utilized by ma/doctoral universities. 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 (3%), college location (3%), college setting (2%), college living plans (2%), recognition of programs (1%), and educational aspirations (1%).

5.1.2 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+."[8] However, Figure 6 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 (32%). 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 7 shows minimum and maximum thresholds used in SAT score filters and 8 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 7, 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.[9]

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

[9] Interestingly, 7% of ma/doctoral universities' SAT filter orders indicated a minimum SAT score threshold

Figure 6: GPA filter used by research vs. ma/doctoral

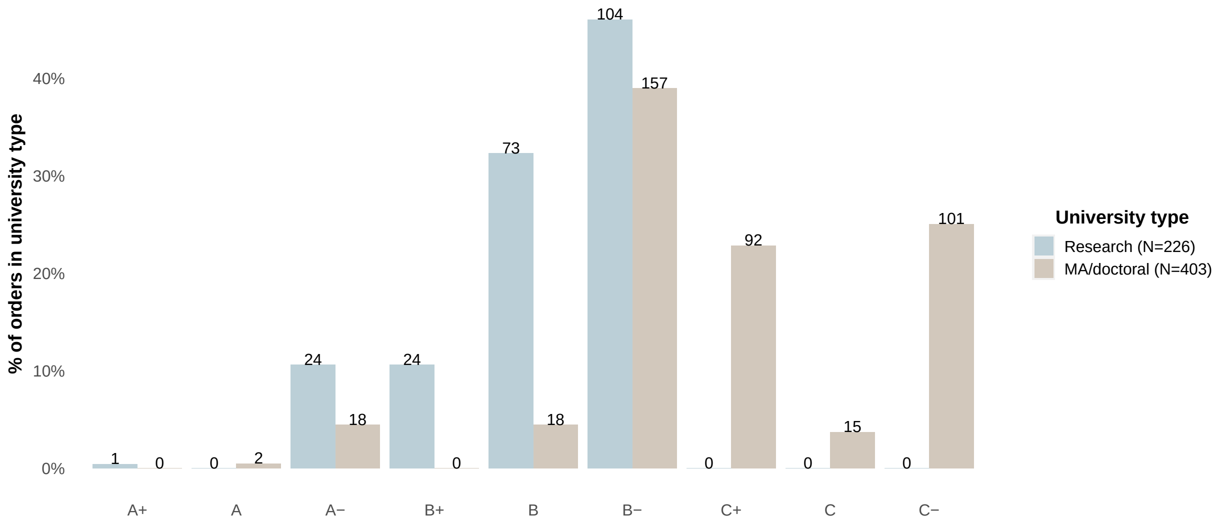
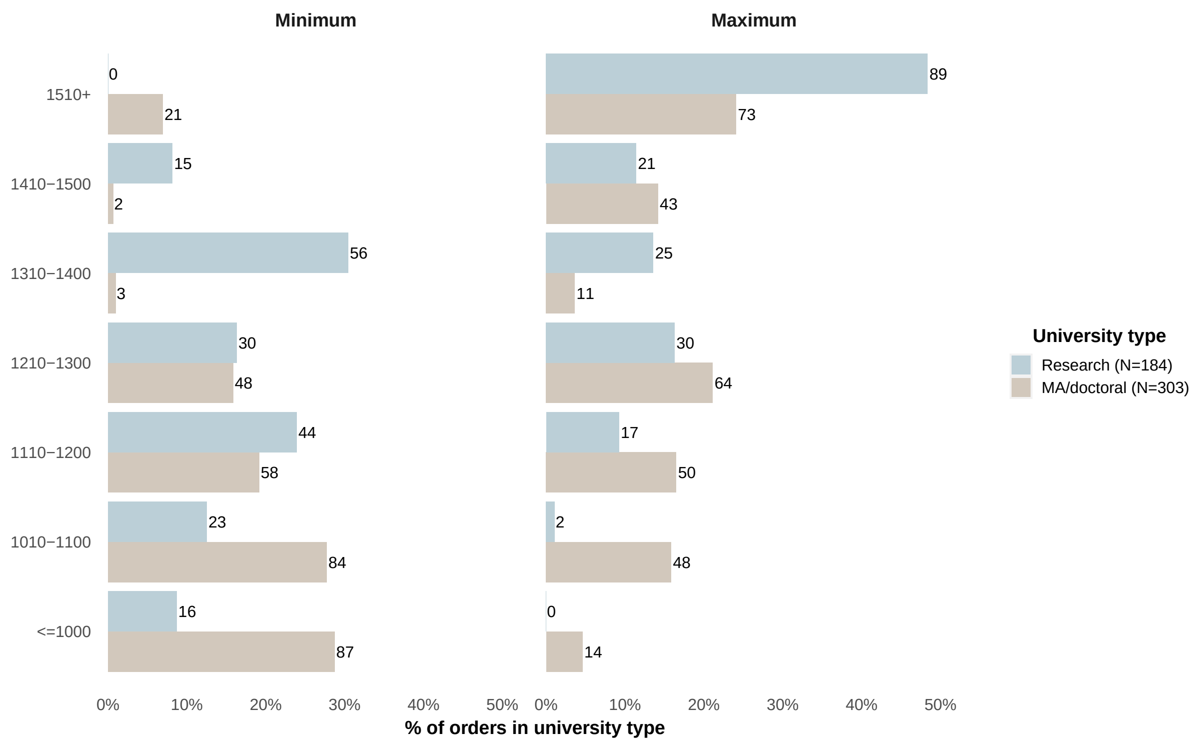


Figure 7: SAT filter used by research vs. ma/doctoral



Note: There were also SAT filters for separate components of the exam (e.g., math, reading, writing), however those were excluded from the figure above. Only the filter criteria for the overall SAT score was considered.

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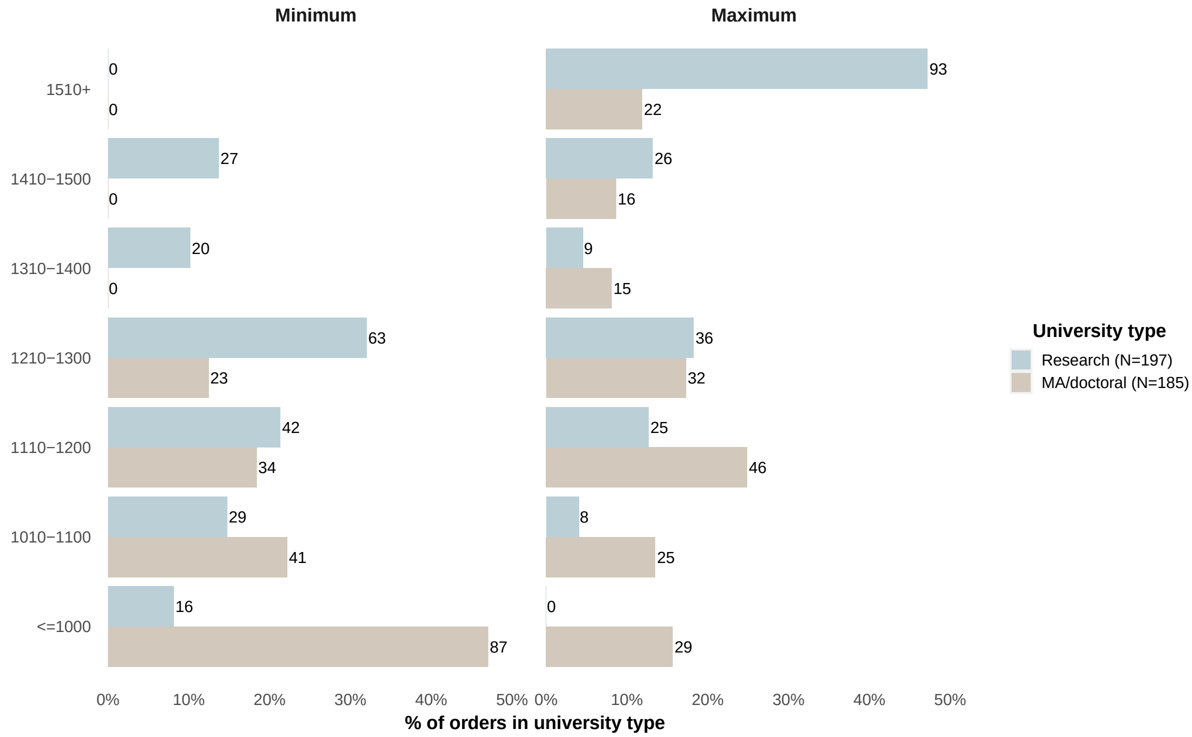
of 1500+, whereas research universities made zero orders at that minimum threshold. These 21 orders were made by two different ma/doctoral universities targeting prospects for specific scholarship programs.

Figure 8: PSAT filter used by research vs. ma/doctoral



5.1.3 Geographic filters

The research universities in our sample used different geographic filters than the ma/doctoral universities in our sample.

Research universities. About 77% of orders by research universities filtered on state (Figure 5). 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 9 and 10 show orders by research universities that filtered on state, with Figure 9 showing orders that filtered on out-of-state prospects and Figure 10 showing orders that filtered on in-state prospects. When filtering for out-of-state prospects, the most commonly filtered states were, California, Texas, Arizona, and Illinois. These orders tended to avoid less populous and less affluent states.

Figure 9: State filter used by research universities, out-of-state

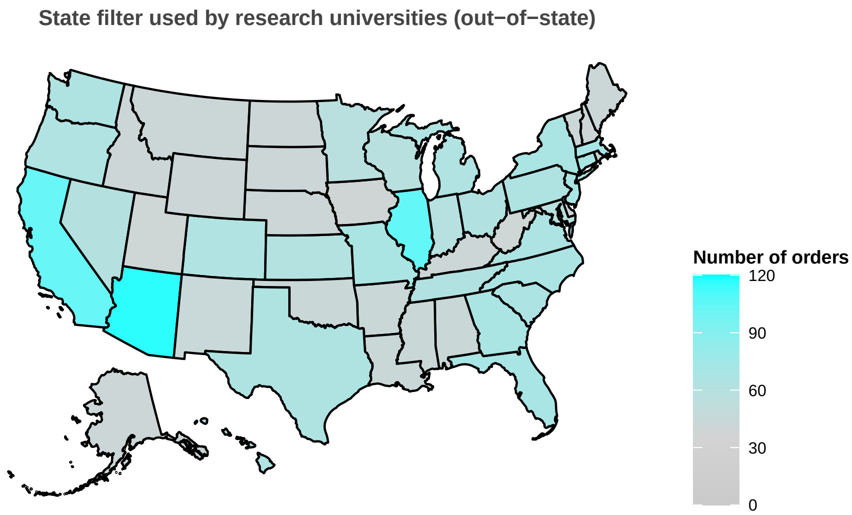
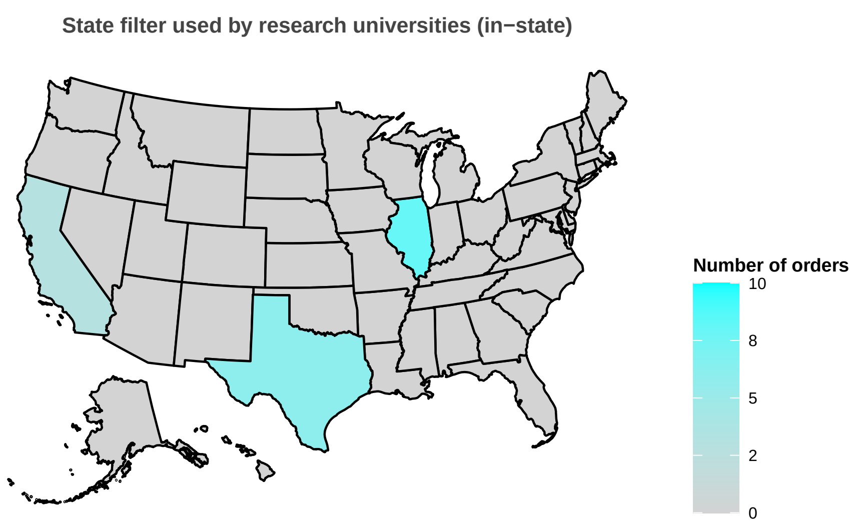


Figure 10: State filter used by research universities, in-state



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 (College Board, 2011a).

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 (College Board, 2011b). 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.

ma/doctoral universities. 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.

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 several attempts for the universities in our sample. We estimate that about 41% (n=157) of the 381 orders using zip codes filtered on five-digit zip code.[10]

While 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.

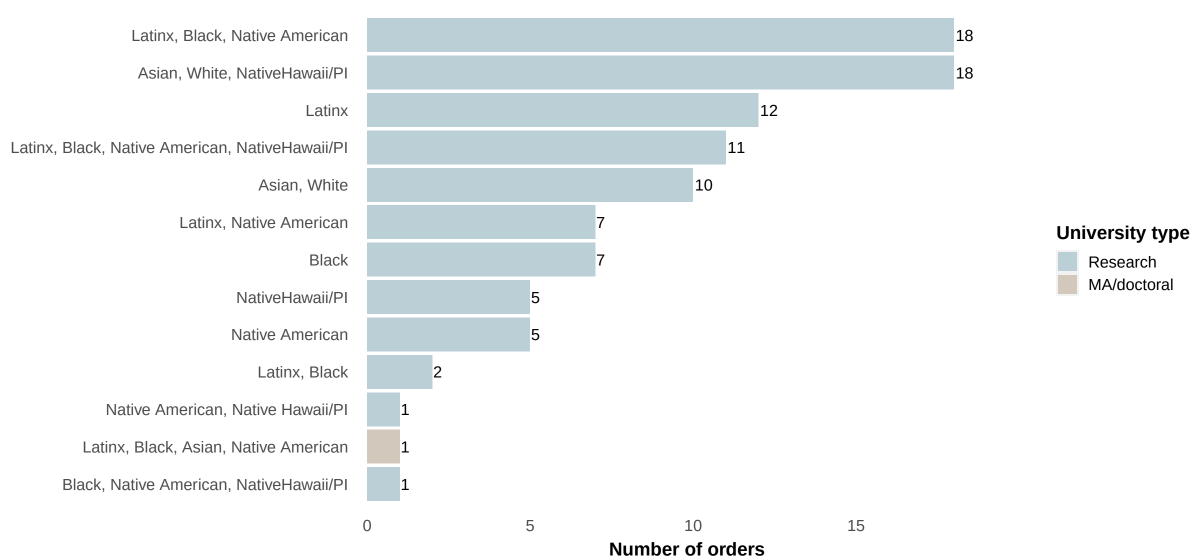
[10]Because orders that did include specific zip code filters (by printing them on the order summary rather than in separate file) were all the three-digit level, we presume that orders using external files for zip code filters were at the five-digit level. For example, one doctoral university gave us 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.

5.1.4 Demographic Filters

Nearly all orders using demographic filters were made by research universities. Figure 11 shows the number of orders that used a race/ethnicity filter. Most of the 98 orders using race/ethnicity filters specified multiple race/ethnicity groups. This includes 18 orders that filtered by Black, Native American, or Latinx prospects and 18 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.

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



5.1.5 Combination of Filters

On average, orders by research universities (N=372) specified five to six filter criteria, whereas orders by ma/doctoral universities (N=458) specified four to five filter criteria. Table 3 shows the ten most commonly used combinations of filters across orders by university type. While the majority orders specified multiple filters as "AND" conditions, some orders specified particular filters as "OR" conditions (e.g., SAT score in some range OR PSAT score in some range). Additionally, it is important to note that filter combinations are skewed by universities that made large numbers of orders relative to other universities (see Figure 4).

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%

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.

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 27 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 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).

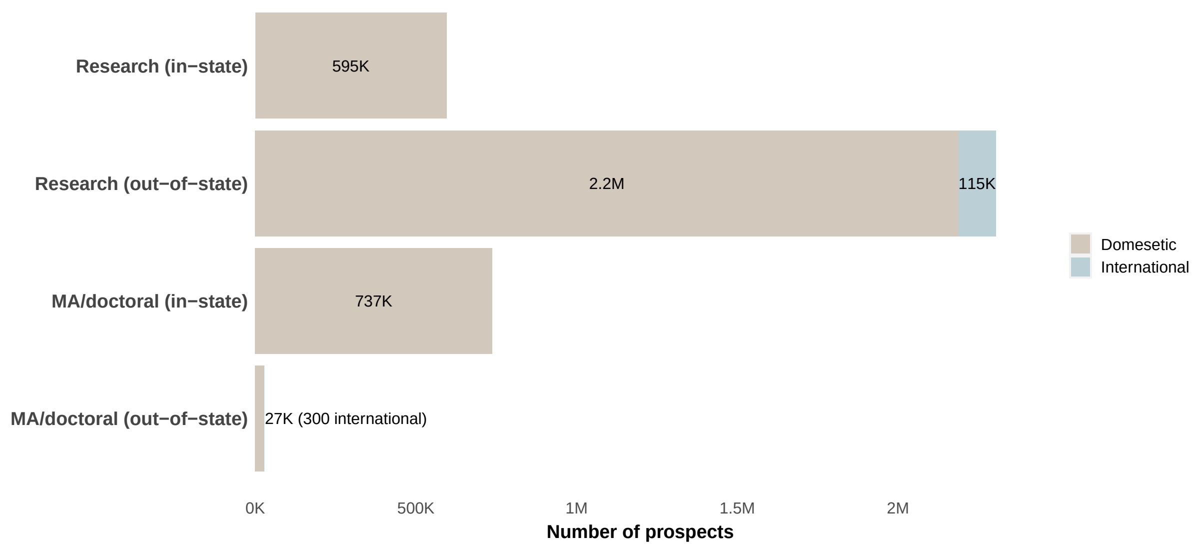
The results for Research Question 3 below investigates the student characteristics associated with particular combinations of filters.

5.2 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 whose profiles were purchased by universities includes 594 orders resulting in 3,663,257 prospects.

Figure 12 shows the number of prospects whose profiles were purchased by in-state versus out-of-state across institutional type. Research universities purchased profiles for many more out-of-state students than ma/doctoral universities. For example, of the nearly 2.9 Million prospects whose profiles were purchased by research universities, 79% were out-of-state, including internationals. For ma/doctoral universities, only 4% of the nearly 765,000 prospects were out-of-state students.

Figure 12: Number of prospects by university type and location



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

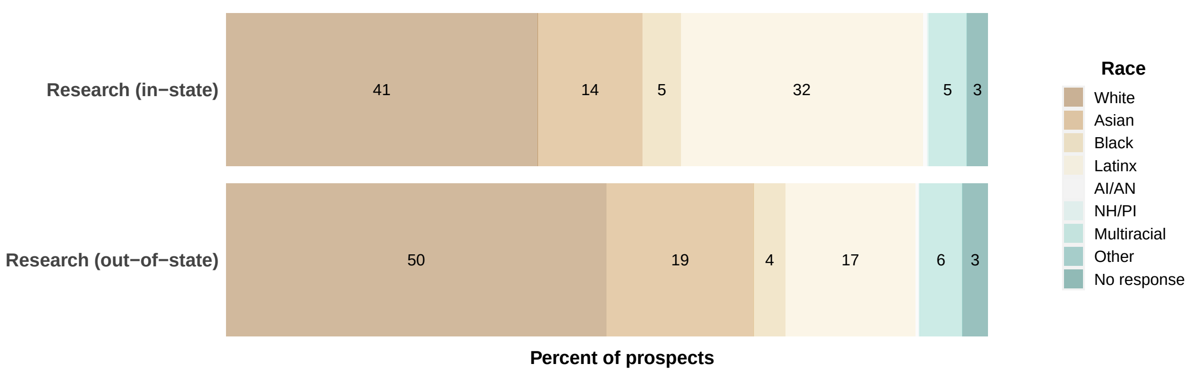
Reporting ethnicity and race. College Board's voluntary demographic questionnaire asks students separate questions about ethnicity (Cuban, Mexican, Puerto Rican, other Hispanic, non-Hispanic, ethnicity non-response) and about race (American Indian or Alaska Native, Asian, Black, Native Hawaiian or other 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" (College Board, 2016). 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 (College Board, 2016). 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."

5.2.1 Public Research Universities

Figure 13 presents the racial characteristics of domestic 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 3% no response. By contrast, in-state prospects were 41% white students, 14% Asian, 32% Latinx, 5% Black, 5% multiracial, and 3% of students that did not report their race/ethnicity.

Figure 13: Racial composition of prospects in lists purchased by research universities



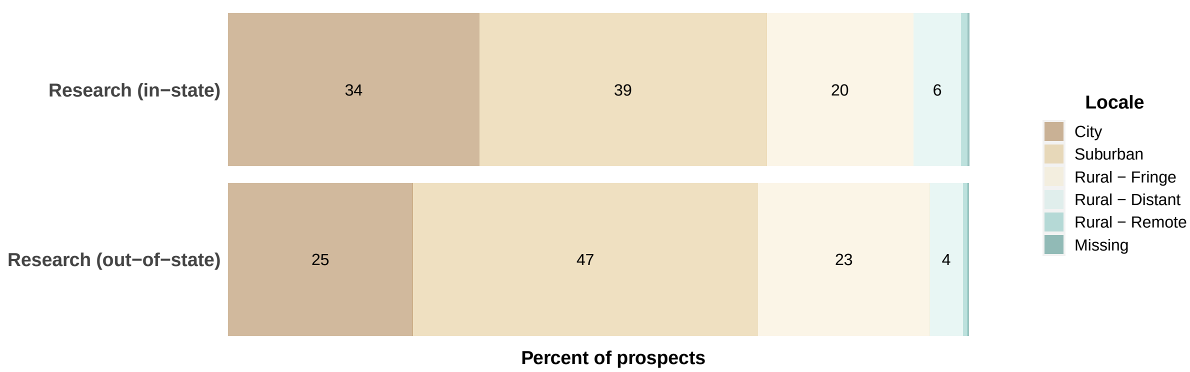
Note: Prospects whose race were unknown (0.4% in-state and 0.6% out-of-state) were excluded.

Figure 14 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 $113,000. In-state prospects lived in zip-codes where the average median household income was $99,000.

Figure 14: Median household income of prospects in lists purchased by research universities

Figure 15 examines the extent to which in-state and out-of-state prospects in lists purchased by research universities tend to reside in urban, suburban, or rural zip codes, as defined by the NCES/Census "locale" variable (Geverdt, 2018). 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 whose profiles were 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."

Figure 15: Locale of prospects in lists purchased by research universities



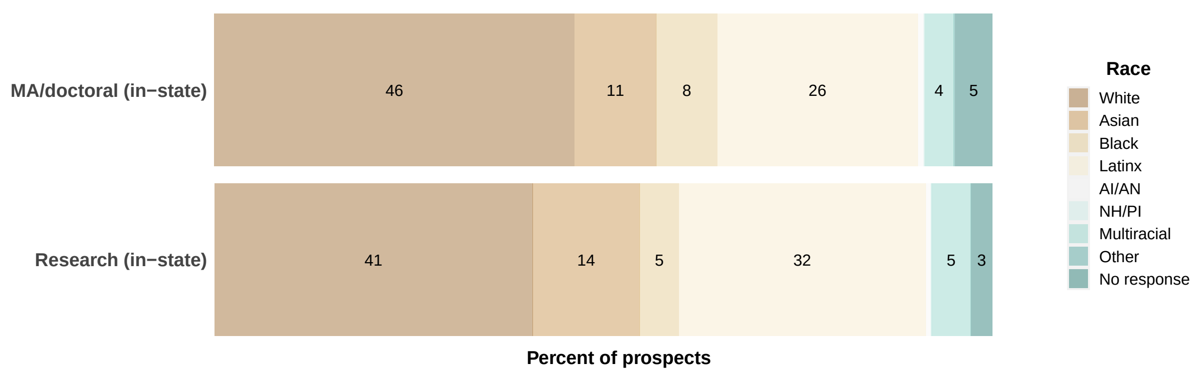
Finally Appendix A6, shows that the percentage of out-of-state prospects attending private high schools (12%) was higher than the percentage of in-state prospects attending private schools (8%).

5.2.2 Public ma/doctoral Universities

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

Figure 16 compares the racial characteristics of in-state prospects included in lists purchased by ma/doctoral universities to the racial characteristics of in-state prospects in lists 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. Although, this is partly a factor of our data collection sample having only research universities for some states and only ma/doctoral universities in other states. For example, ma/doctoral universities' in-state prospects are 46% White, 11% Asian, 8% Black, 26% Latinx, 0.8% 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, 0.6% American Indian/Alaska Native, 0.2% Native Hawaiian/Pacific Islander, 5% multiracial, and 3% did not report their race/ethnicity.

Figure 16: Racial composition of prospects in lists purchased by ma/doctoral universities



Note: Prospects whose race were unknown (0.4% ma/doctoral and 0.4% research) were excluded.

Figure 17 compares the household income of in-state prospects in lists purchased by ma/doctoral universities to that of in-state prospects in lists 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 in lists purchased by research universities were slightly more affluent, living in zip codes where the average of median household income was $99,000.

Figure 17: Median household income of prospects purchased by ma/doctoral universities

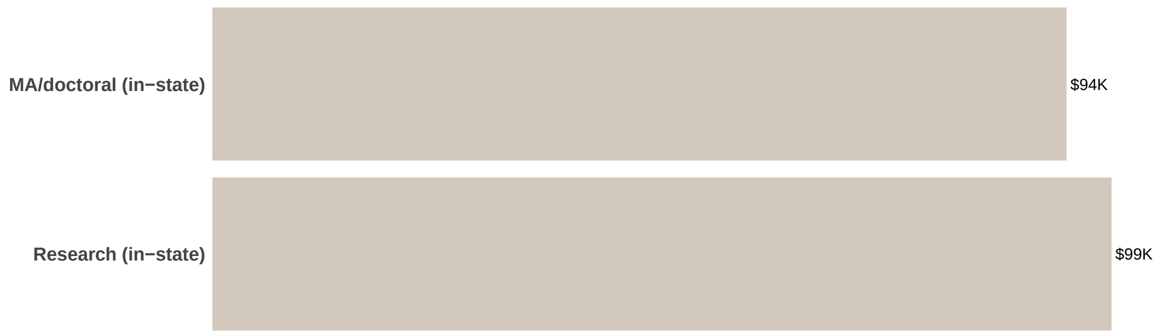
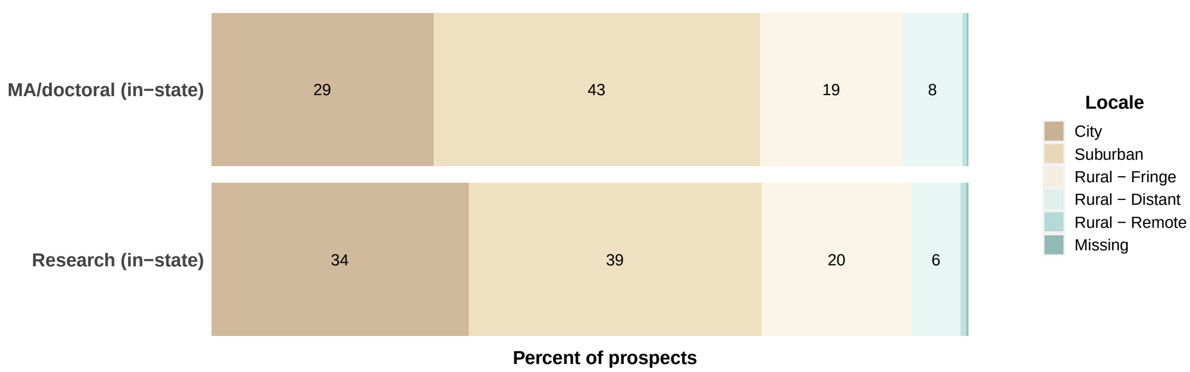


Figure 18 examines the locale (city, suburban, rural) of in-state prospects. Compared to research universities, ma/doctoral universities purchased lists with a slightly higher percentage of prospects living in suburban areas (43% compared to 39%) and a slightly lower percentage of prospects living in cities (29% compared to 34%). The share of prospects residing in rural areas was nearly identical across university type.

Figure 18: Locale of prospects in lists purchased by ma/doctoral universities



5.3 Filter Criteria and Characteristics of Prospects

We analyze the relationship between filter criteria and the characteristics of prospects whose profiles were purchased 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.

Next, in what we view as the most important analyses of the report, we analyze the characteristics of prospects in orders that used particular combinations of filters that are commonly observed or thematically important. In particular, we present four "deep dives": zip code & test score filters; geodemographic Segment filters; women in STEM; and targeting URM students. These analyses contextualize the characteristics of prospects whose profiles were purchased by showing the characteristics of comparison groups in particular metropolitan areas.

5.3.1 Prospect Characteristics Across Individual Filters

Table 4 presents the characteristics of prospects by individual filters. For each column, averages are reported across all prospects whose profiles were purchased via orders using the specified column filter, which includes orders that used the specified filter in combination with other filters.[11]

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
% AI/AN	1	1	1	0	1	1	1	1	0	0	0	2	0
% NH/PI	0	0	0	0	0	1	0	0	0	0	0	0	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

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. Orders that specify a gender filter result in prospect lists that are 7% Black, Latinx, and/or Native American. This percentage is also relatively low for prospect lists that use segment or CBSA filters (14% and 11%, respectively). However, racial disparities are not as large for orders using a PSAT filter (24% Black, Latinx, Native America). 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 result is consistent with RQ1 (above), which found that more than half

[11] 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 3,663,257 prospects.

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 $135,000. Similarly, orders using AP scores and race/ethnicity filters showcased the lower extreme at $90,000 and $94,000, respectively.

Orders using geographic filters result in specific patterns of in-state versus out-of-state prospects. 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 CBSA, segment, and geomarket filters are likely used for targeting out-of-state students, as the use of these filters result in prospect lists made up of 96%, 85%, and 83% 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. 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).

With respect geographic locale, the percentage of prospects living in rural-fringe localities was quite stable across filters. Orders that utilized Segment, CBSA, or gender filters had lower percentages of students living in rural-distant than other filters.

5.3.2 Zip Code & Test Score Filters

One common combination of filters used across orders were zip codes and test score ranges. Often, these orders specified five-digit zip codes in a separate file provided to the College Board.[12] We conduct an analysis using a hypothetical zip code filter to investigate the extent to which filtering prospects by five-digit zip-code can yield racial disparities.

To do this, we analyze four student lists purchased by one research university. Each of these these four orders targeted students in CA, but specified different SAT/PSAT score ranges (Note: this university made a total of 37 orders targeting CA high school students graduating in 2019-2022, with 20 of these orders only using PSAT or SAT filters in addition to the state

[12] We obtained order summaries from several universities that indicated filtering by five-digit zip code, but we were unsuccessful in acquiring the student list data and the additional files listing five-digit zip code filters for these orders after several attempts. In the process of requesting the additional data and files, several universities using zip code filters revealed that they were not in possession of the files because student list purchases were made by a third-party enrollment management consulting firm on their behalf and that the firm possessed the files.

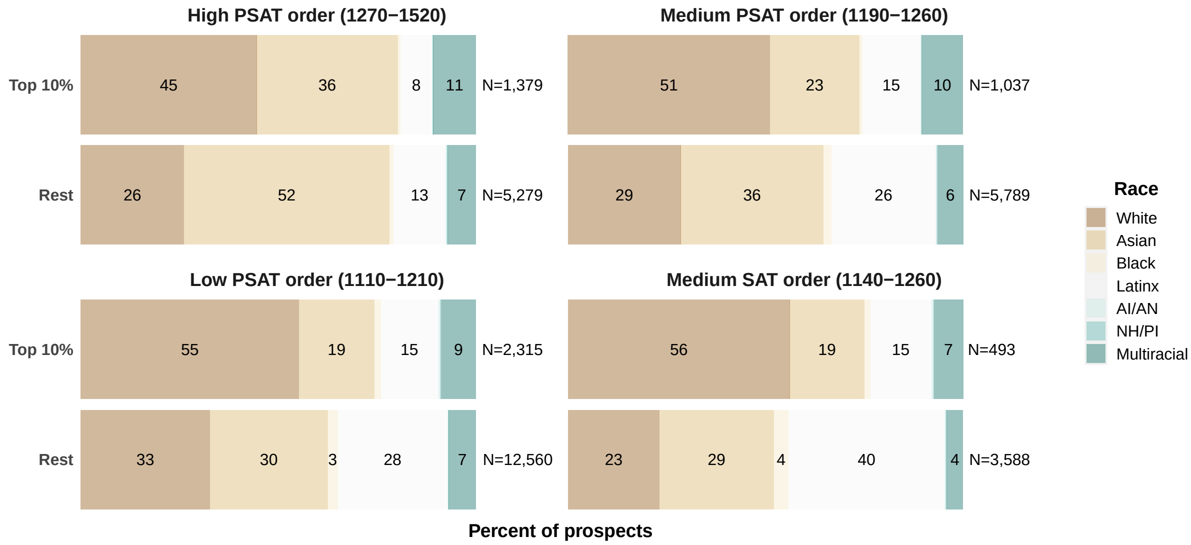
and high school graduating class). Within these four student list purchases, we focus on prospects from the Los Angeles metropolitan area.

Next, we apply a hypothetical five-digit zip code filter and categorize prospects from Los Angeles 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.

Drawing from research which finds that recruiting efforts by selective private universities and out-of-state recruiting by public research universities focuses on affluent communities (Jaquette et al., forthcoming; Salazar, 2022; Salazar, Jaquette, & Han, 2021), our hypothetical zip code filter targets zip codes in the top 10% (n=38) of median household income of the 378 zip codes in the Los Angeles metropolitan area. These top 10% zip codes range from $140,000 to $249,000 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 $25,000 to $138,000 in median household income and encompass areas like East L.A., Whittier, and Pasadena.

Figure 19 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, 1,379 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, 5,279 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.

Figure 19: Los Angeles prospects from top income decile zip codes (racial composition)



Note: Prospects whose race were unknown (1% top decile and 0.9% rest for high PSAT orders; 0.9% top decile and 0.9% rest for medium PSAT orders; 0.6% top decile and 0.6% rest for low PSAT orders; 0% top decile and 0.3% rest for medium SAT orders) or did not report their race (5% top decile and 4% rest for high PSAT orders; 4% top decile and 4% rest for medium PSAT orders; 4% top decile and 3% rest for low PSAT orders; 4% top decile and 3% rest for medium SAT orders) were excluded.

Figure 19 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, 45% White, 36% Asian, 11% Multiracial, 8% Latinx, 0.7% Black, and 0.2% Native American. However, prospects excluded by the zip code filter and not in the student list purchased by the university would be 26% White, 52% 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. Of these prospects, the 1,037 prospects living in a top income decile zip code are 51% White, 23% Asian, 15% Latinx, 10% Multiracial, 0.8% Black, and 0.3% Native American. By contrast, the 5,789 of the 6,826 prospects that would have been excluded from the hypothetical zip code filter contain a larger proportion of Asian (36%) and Latinx (26%) prospects.

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 2,315 prospects still included in the student lists after applying the zip code filter are, on average, 55% White, 19% Asian, 15% Latinx, 9% Multiracial, 2% Black. However, the 12,560 prospects excluded by the zip code filter and not included in lists purchased by the university are, on average, 33% White, 30% Asian, 28% Latinx, and 3% Black.

Figure 19 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 19 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=493) after applying the zip code filter are, on average, 56% White, 19% Asian, 15% Latinx, 7% Multiracial, 1% Black, and 0.4% Native American. However, Latinx (40%), Asian (29%), 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=3,588).

5.3.3 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 College Board (2011b):

> 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" (College Board, 2011b, 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). College Board (2011b) (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" (College Board, 2011b, 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 the profiles of 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 College Board (2011b), 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 eight 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 prospects whose profiles were purchased.

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.[13] Prospects were also geographically filtered across State/CBSAs and segments. Several large CBSAs were consistently targeted across orders (including but not limited

[13] 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**

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

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 20 compares racial and income the characteristics of prospects whose profiles were purchased to the characteristics of all high school students. We show four metropolitan areas, where many prospects whose profiles were purchased reside: New York (27,932 prospects, rank #1), Los Angeles (12,307 prospects, rank #2), Philadelphia (9,126 prospects, rank #3), Washington, DC (5,728 prospects, rank #4). For each metropolitan area, we show two figures: on the left column, we show the racial composition of prospects whose profiles were purchased 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 prospects whose profiles were purchased 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.

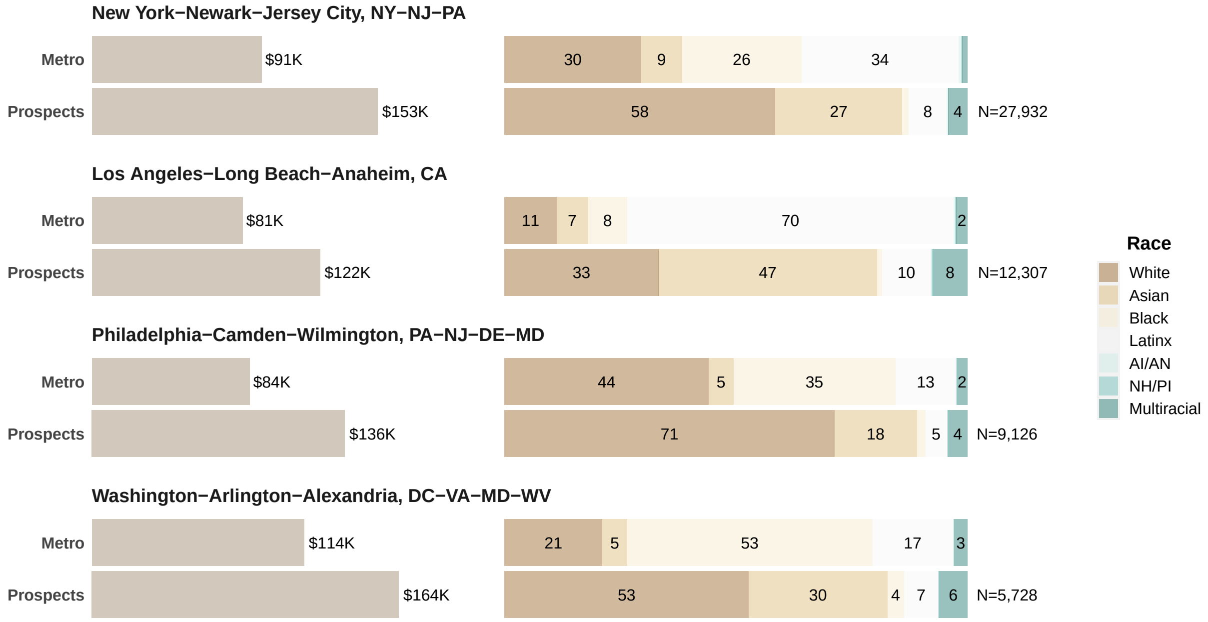
For New York, Figure 20 shows White and Asian students comprised 58% and 27% of prospects whose profiles were purchased, respectively, compared to 30% and 9% of students in public high schools. By contrast, Black and Latinx students comprised just 1% and 8% of prospects, respectively, compared to 26% and 34% of students in public high schools. Furthermore, prospects whose profiles were purchased lived in zip codes that were much more affluent – an average of $153,000 – than the overall New York metropolitan area median income of $91,000.

Figure 20 shows similar patterns for race in other three metropolitan areas. The race results for Philadelphia were particularly egregious, with Black and Latinx students representing 35% and 13% of public high school students, respectively, but only 2% and 5% of prospects whose profiles were purchased. Wide income disparities were present across metropolitan areas. In Washington, DC, 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.

Figure 21 takes a spatial look at the the high schools presented in Figure 20 for the Philadelphia metropolitan area, with shaded zip codes according to median household income and racial/ethnic composition. The map shows public high schools, with blue markers indicating the location of a school where at least one prospect's profile was purchased and the size of blue markers indicating the number of prospects whose profiles were purchased. Red markers indicate the location of schools where no prospect profiles were purchased. Figure 21 corroborates descriptive findings above. Prospects from Philadelphia whose profiles were purchased attend high schools that are largely concentrated in affluent and predominantly White zip codes bordering the central core of the metropolitan area, whereas school where zero prospect profiles were purchased are concentrated in the lowest income areas with larger proportions of People of Color in the center metropolitan area. Similar patterns are evident in maps of the other three metropolitan areas, which can be accessed here.

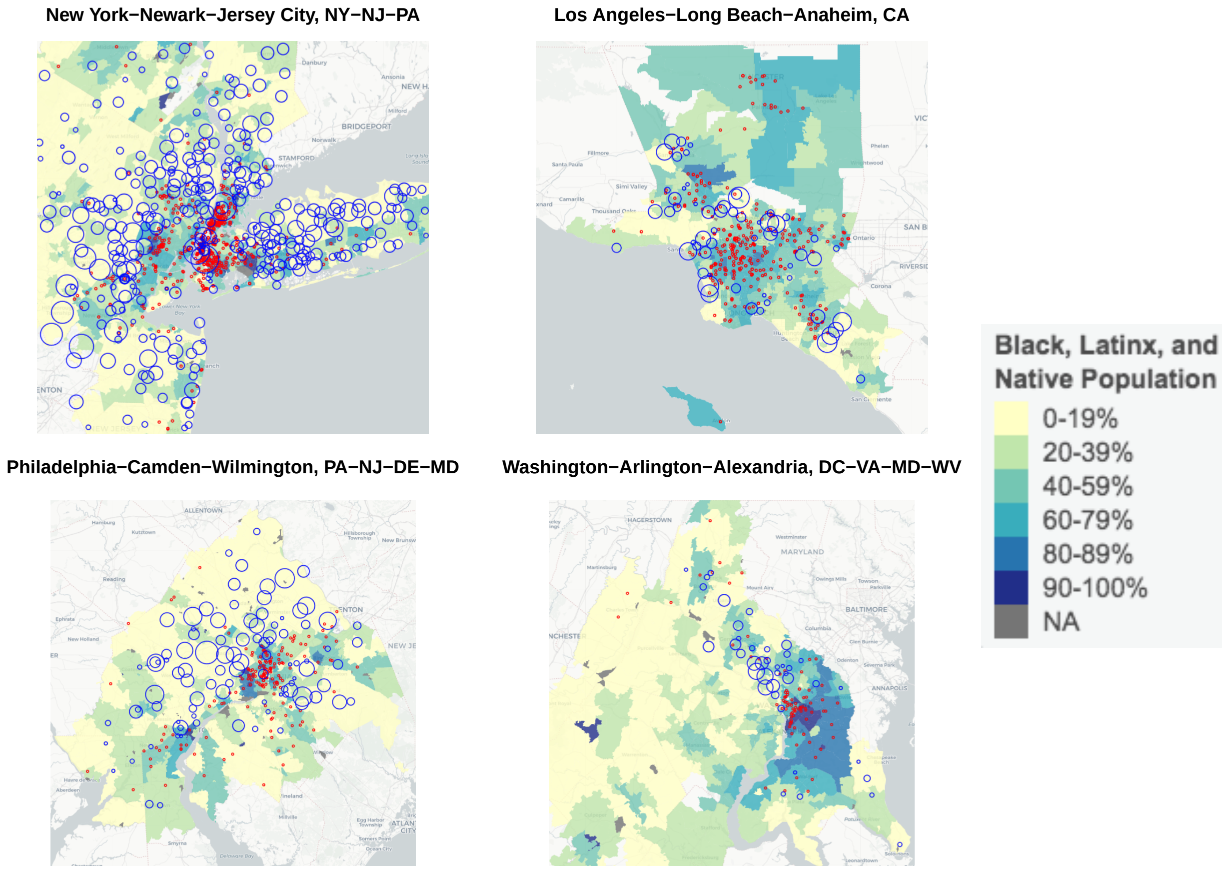
To what extent are these income disparities driven by the use of geodemographic Segment filters versus the other filters (e.g., SAT/PSAT score ranges) utilized in these orders? The data we obtained via public records requests cannot address this question. However, the racial and income inequalities observed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

Figure 20: Segment filter prospects by metro (average income and racial composition)



Note: Public high schools that satisfied the following criteria were included: enrolls at least ten 12th graders; is a non-virtual school; is an open, new, or reopened school. The university provided race data for each student using one or more of the following categories: American Indian or Alaska Native, Asian, Black or African American, Native Hawaiian or other Pacific Islander, White, or missing value. They also provided whether each student is of Hispanic origin by indicating: Yes, No, or missing value. To assign each student a single race/ethnicity category for the analysis, the following logic was used: Latinx if Hispanic origin indicator was a Yes; Multiracial if Hispanic origin indicator is not a Yes and more than one race categories were indicated; each respective race category if Hispanic origin indicator is not a Yes and only that one race category was indicated; No response otherwise. Prospects who did not report their race (3% from NY; 3% from LA; 2% from Philly; 3% from DC) were excluded.

Figure 21: Segment filter prospects by metro maps (average income and racial composition)



Note: Public high schools that satisfied the following criteria were included: enrolls at least ten 12th graders; is a non-virtual school; is an open, new, or reopened school.

5.3.4 Women in STEM

Two research universities in the study made orders targeting prospects who are women interested in science, technology, engineering, and math (STEM). We analyze orders by one university, which targeted women interested in STEM via two different filter patterns:[14]

- 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.

[14] Orders by the second university utilized similar criteria, 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).

- 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.[15] Orders for out-of-state prospects filtered for scores ranging from 4 to 5 on AP STEM tests.

We analyze the resulting student lists from Women in STEM orders – focusing on prospects from four metropolitan areas – 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.

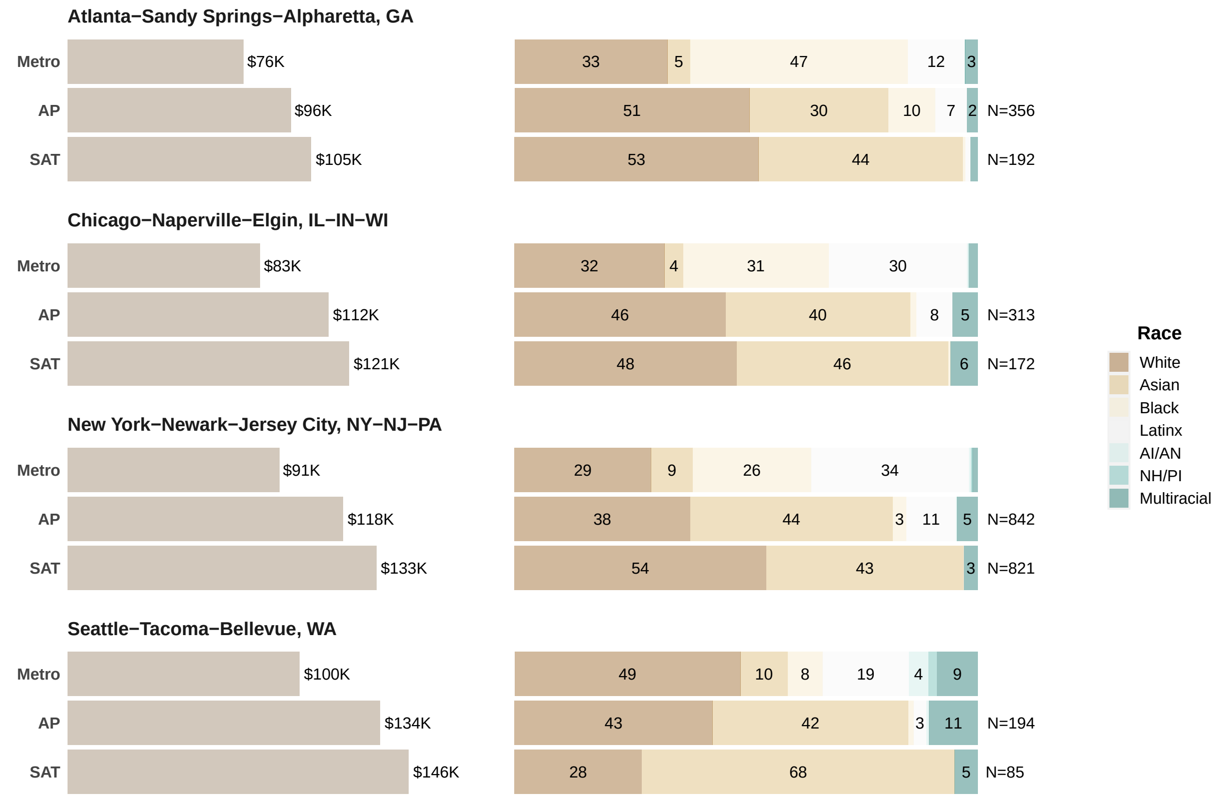
The university made a total of 11 orders in March 2020 targeting women in STEM, which resulted in 12,938 prospects whose profiles were purchased. Six of the 11 orders targeted out-of-state prospects, with three orders using SAT scores plus major interests and three orders using AP scores. Because nearly 85% of prospects from Women in STEM orders were 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.[16] The four out-of-state metropolitan areas were selected based on where the greatest number of prospects whose profiles were purchased and based on regional variation: New York (1,663 prospects, rank #1), Atlanta (548 prospects, rank #2), Chicago (485 prospects, rank #3), and Seattle (279 prospects, rank #11).

Figure 22 compares racial and income characteristics of prospects whose profiles were purchased to the characteristics of all female public high school students in each metropolitan area. For each metropolitan area, we show two figures. The figure on the left column provides the average median household income for the overall metropolitan area, for prospects whose profiles were purchased using AP scores, and prospects whose profiles were purchased using SAT scores. 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 12th grade students in the metropolitan area, of prospects whose profiles were purchased using AP scores, and of prospects whose profiles were purchased using SAT scores.

[15] 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

[16] In-state prospects were targeted across five orders, three of which used AP scores and two of which used SAT scores with major interests. Three of the 11 orders resulted in student lists with zero prospects. Two of these zero prospect orders 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.

Figure 22: Women in STEM prospects by metro (average income and racial composition)



Note: Public high schools that satisfied the following criteria were included: enrolls at least ten female 12th graders; is a non-virtual school; is an open, new, or reopened school. Prospects whose race were unknown (0.6% AP and 0.5% SAT from Atlanta; 1% AP and 0% SAT from Chicago; 1% AP and 0.2% SAT from NY; 3% AP and 0% SAT from Seattle) or did not report their race (2% AP and 3% SAT from Atlanta; 5% AP and 0.6% SAT from Chicago; 4% AP and 6% SAT from NY; 5% AP and 6% SAT from Seattle) were excluded.

Figure 22 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 whose profiles were purchased by the university across both types of orders are more affluent. 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 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 whose profiles were purchased through SAT filters having the highest overall incomes. For Chicago, prospects whose profiles were 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 whose profiles were purchased via AP ($34,000) and SAT filters ($46,000) is most pronounced for Seattle.

Figure 22 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 STEM prospects from New York that scored a 4 or 5 on an AP STEM exam whose profiles were purchased by the university are 38% White, 44% Asian, 3% Black, 11% Latinx, 5% multiracial. Only 2 women in STEM prospects in the New York metro whose profiles were purchased via AP scores identified as Native American. These racial disparities are most pronounced in orders using SAT scores. Of the 821 prospects from the New York metro that scored a 1200 to 1600 on the SAT and indicated an interest in STEM majors, 54% were White, 43% Asian, and 3% multiracial. Only one prospect identified as Latinx and zero prospects identified 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 whose profiles were purchased via AP scores (N=356) are 51% White, 30% Asian, 10% Black, 7% Latinx, and 2% multiracial. Most concerning, prospects whose profiles were purchased via SAT scores and STEM major interests (N=192) are 53% White, 44% 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% or less of prospects whose profiles were purchased via both AP and SAT filters 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 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.

5.3.5 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 11, commonly observed filters were Latinx/Black/AIAN (N=18 purchases) and Asian/White/NHPI (N=18). 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 (e.g., lack of racial diversity in college enrollments) may lead to other problematic inequities (e.g., failing to recruit Students of Color from predominantly non-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 prospects whose profiles were purchased: 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 23 examines the race and ethnicity of prospects whose profiles were purchased 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 23. 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.

For the Houston metro area, the aggregate race/ethnicity column (left) of Figure 23 shows that 74% of the 371 prospects whose profiles were purchased were categorized as Latinx, 18% Black, 1% AI/AN, and 5% multi-racial. The right hand column allows each prospect to identify with multiple racial groups. For these same 371 prospects, 59% identified as White, 23% as Black, 4% as Asian, and 13% AI/AN. Thus, the aggregate race/ethnicity column (left) understates the number of prospects who identify as Black and dramatically understates the number of prospects who identify as AI/AN.

Figure 23: Race and ethnicity variables, aggregated vs. alone

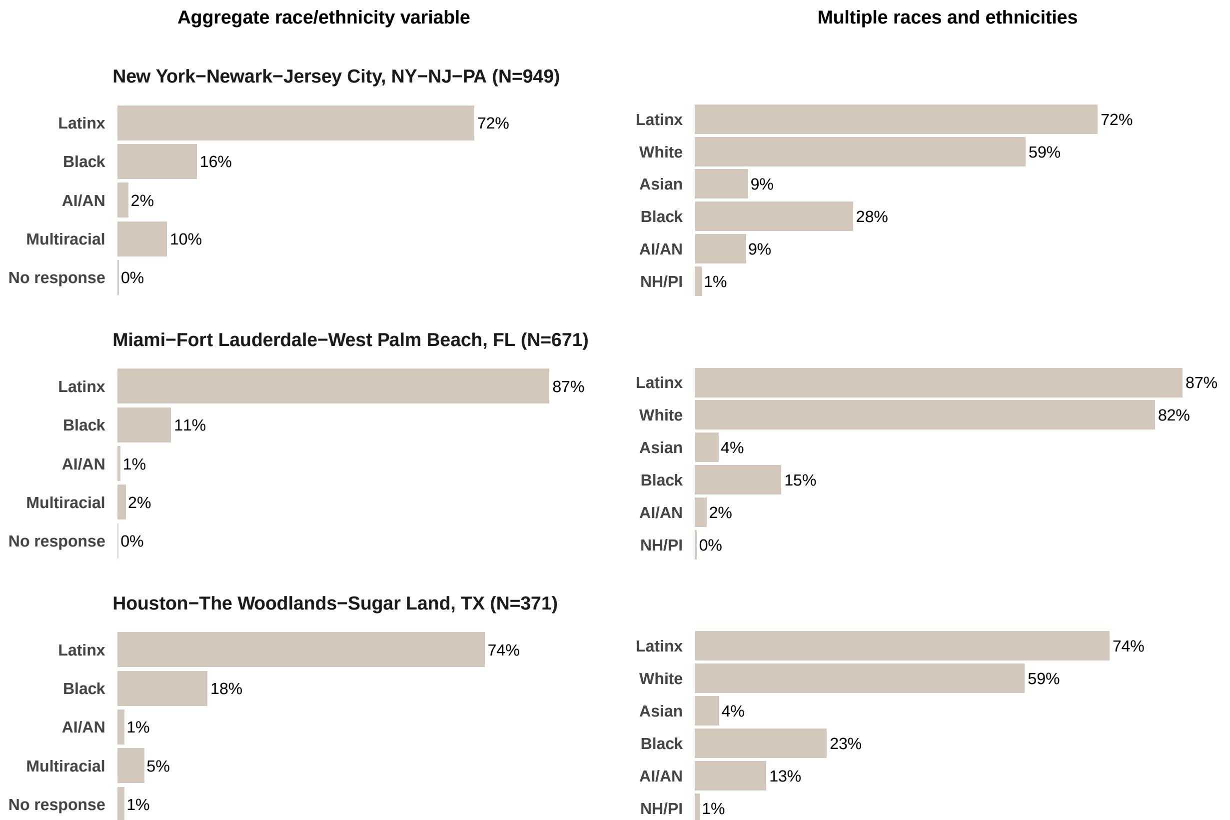
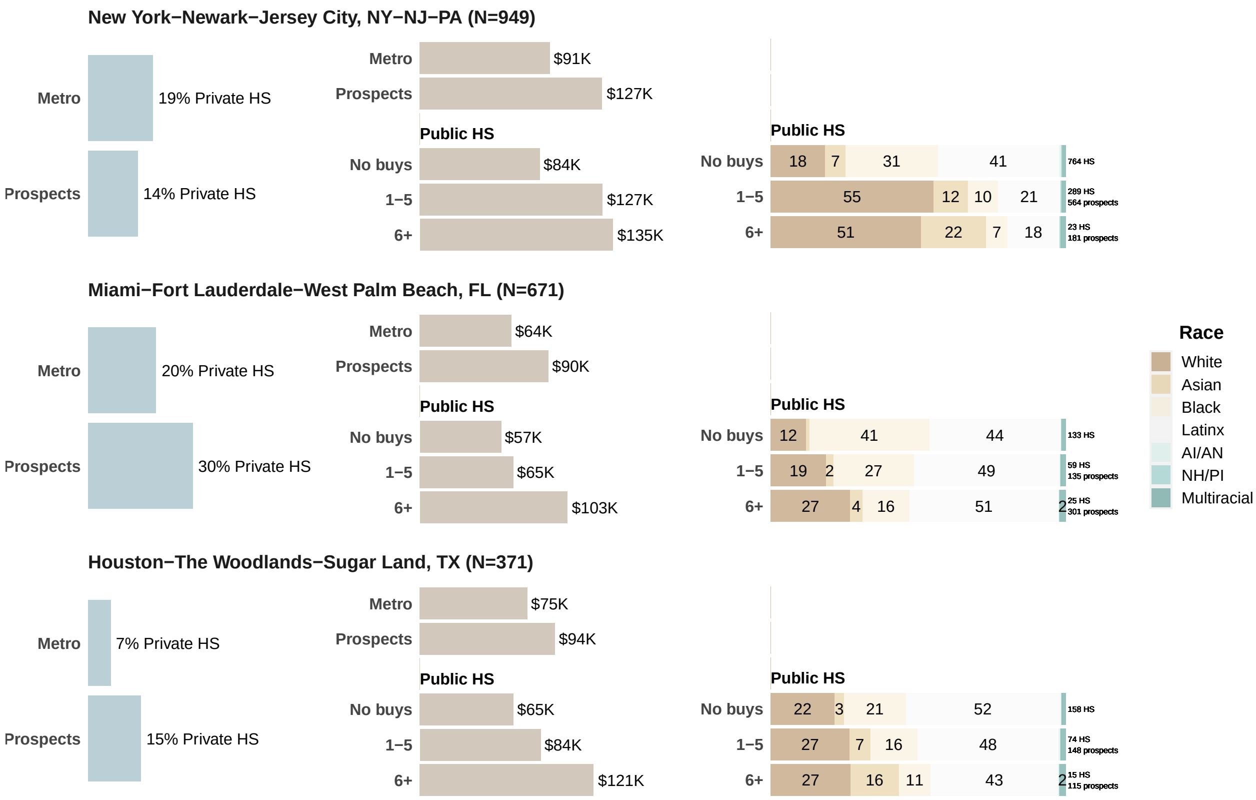


Figure 24 describes the high schools these prospects attended. The left column examines attendance at public and private schools. For example, across the New York CBSA, 19% percent of high school students attended a private high school compared to 14% of prospects whose profiles were purchased.

The middle column examines household income. Prospects whose profiles were 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 prospect profiles purchased and greater than six prospect profiles purchased 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 prospect profiles were purchased ($84,000).

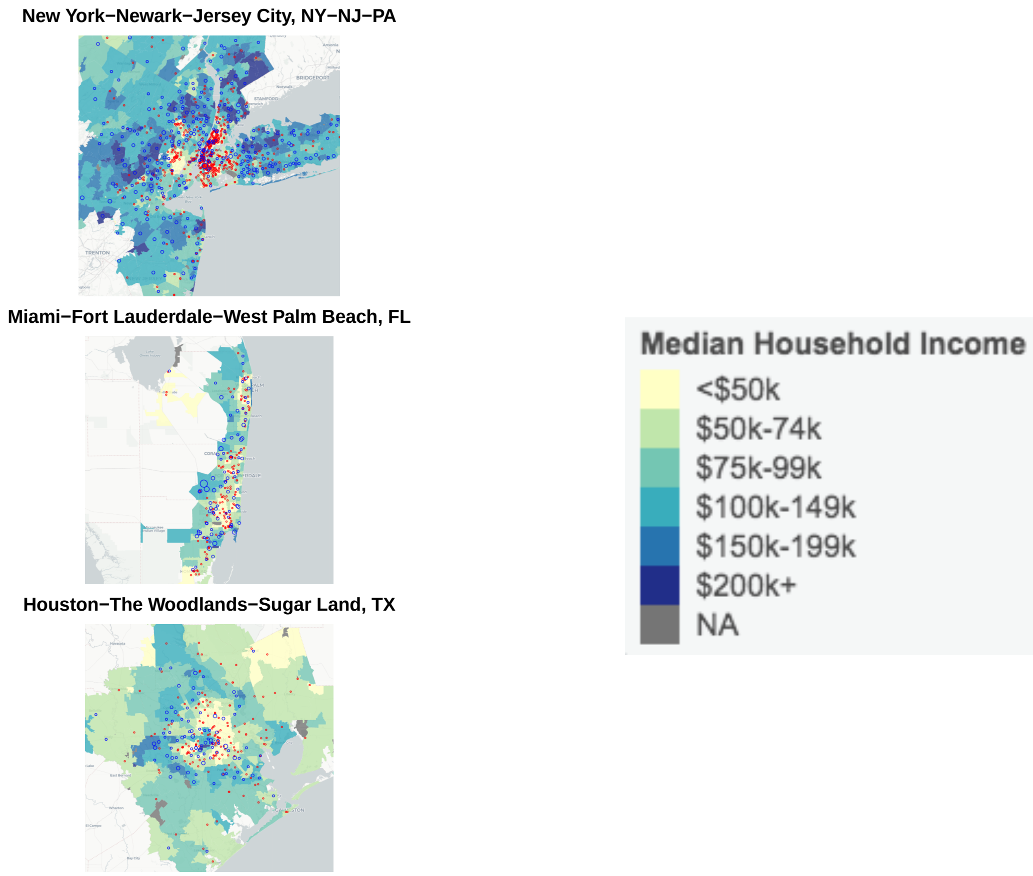
The right column examines the race/ethnicity composition of public and private high schools. For example, New York CBSA public high schools where no prospect profiles were purchased were, on average, 31% Black, 41% Latinx, 18% white, and 7% Asian. On the other hand, public high schools with one to five purchased prospect profiles were on average, 10% Black, 21% Latinx, 55% white, and 12% Asian.

Figure 24: Purchased profiles for students of color by metro (HS type, average income, racial composition)



Note: Public high schools that satisfied the following criteria were included: enrolls at least ten 12th graders; is a non-virtual school; is an open, new, or reopened school. Private high schools that satisfied the following criteria were included: enrolls at least ten 12th graders.

Figure 25: Purchased profiles for students of color by metro maps (average income and racial composition)



Note: Public high schools that satisfied the following criteria were included: enrolls at least ten 12th graders; is a non-virtual school; is an open, new, or reopened school. Private high schools that satisfied the following criteria were included: enrolls at least ten 12th graders.

Results for Miami differed from New York. Figure 24 shows the differences in household income were less pronounced than the case of New York. However, public high schools with greater than six purchased prospect profiles had an average household income of $103,000 relative to $57,000 for public high schools where no prospect profiles were purchased. With respect to the racial composition of public schools, schools with at least one prospect profile purchased tended to enroll a higher number of Latinx students but a lower number of Black students than schools with no prospect profiles purchased. At the same time 30% of prospects from Miami whose profiles were purchased attended a private high school.

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

Figure 25 takes a spatial look at the the high schools presented in Figure 24 for the New York metropolitan area, with shaded zip codes according to median household income and racial/ethnic composition. The map shows public high schools, with blue markers indicating the location of a school where at least one prospect profile was purchased and the size of blue markers indicating the number of prospect profiles purchased. Red markers indicate the location of schools where no prospect profiles were purchased. Figure 25 corroborates descriptive findings above. Prospects from New York whose profiles were purchased attend high schools that are largely concentrated in affluent and predominantly White zip codes around the center metropolitan area, whereas schools where zero prospect profiles were purchased are concentrated in the lowest income areas with larger proportions of People of Color in the center metropolitan area. Similar patterns are evident in maps of the other two metropolitan areas, which can be accessed here.

Results for these three metropolitan areas suggests that student list 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, seemingly a function of local school segregation patterns. In New York – and also Philidelphia and Chicago (results not shown) – prospects whose profiles were purchased tended to attend predominantly white high schools, while public schools with with zero purchased prospect profiles enrolled predominantly non-white students. By contrast, in Miami and Houston – and also Atlanta (results not shown) – prospects whose profiles were purchased attended schools with larger shares of non-white students. However, even in these metropolitan areas, schools with at least one purchased prospect profile tended to have lower enrollment of Black students than schools with zero purchased prospect profiles.

6 Discussion

Recent research suggests that student lists are important for the college access and graduation outcomes of millions of students each year (Howell et al., 2021; Moore, 2017). The results of this study suggest that College Board and ACT student list products, which have dominated the market for decades, may 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 (Cook & Turner, 2019). 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 (Gagnon & Mattingly, 2016; Theokas, 2013).

Research question 2 asks, what are the characteristics of prospects included in student lists purchased? The ma/doctoral universities in our sample primarily purchased student lists with in-state prospects. Similar to our analysis of off-campus recruiting visits (Salazar et al., 2021), research universities in our sample purchased lists with 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 than 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 with many prospects. We also collected data about student lists purchased from ACT and other vendors (and also data about off-campus recruiting visits). Future research will focus on investigating whether patterns found in this study are consistent across a larger number of universities and across student list data purchased from other vendors.

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. These data could answer questions our data collection cannot, such as how do student list purchases – number or orders, search filters, volume of names – differ by more granular characteristics 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? 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 prospects whose profiles were purchased? Because this question is about student list products rather than university behavior, our data collection provides firmer ground from an external validity perspective given a particular set of filter criteria will yield the same set of prospects regardless of which university places the order.[17]

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 along with PSAT and SAT filters across all score ranges (low, moderate, high) leads to substantial declines in the racial diversity of prospects. Second, analyses of filter combinations that use the segment product revealed troubling patterns of racial and socioeconomic exclusion across metropolitan areas. Combinations that included demographic filters (gender, race/ethnicity) were also concerning. Orders that filtered for underrepresented students of color with relatively high test scores tended to target affluent students, who often attended predominantly white high schools. Orders that targeted women in STEM based on AP and SAT scores resulted in student lists with predominantly, and in some cases exclusively, highly affluent, White and Asian prospects.

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, so that universities can more easily purchase only the profiles 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" (College Board, n.d.) while ACT Encoura uses the tag-line "find and engage your best-fit students" (Encoura, n.d.). 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.

[17] One caveat to this statement is that most student list products enable universities to exclude prospects that were included in a previous order

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 (College Board, 2021b). 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 et al. (2022) argue 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.

7 Appendix

Figure A1: Example College Board order summary

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

[redacted]

My Searches, Orders & Files

Print

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

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

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

Figure A2: University by carnegie classification

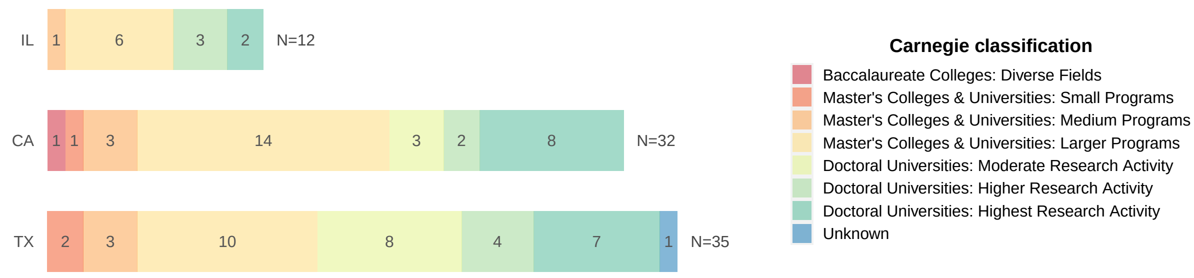


Figure A3: University by locale

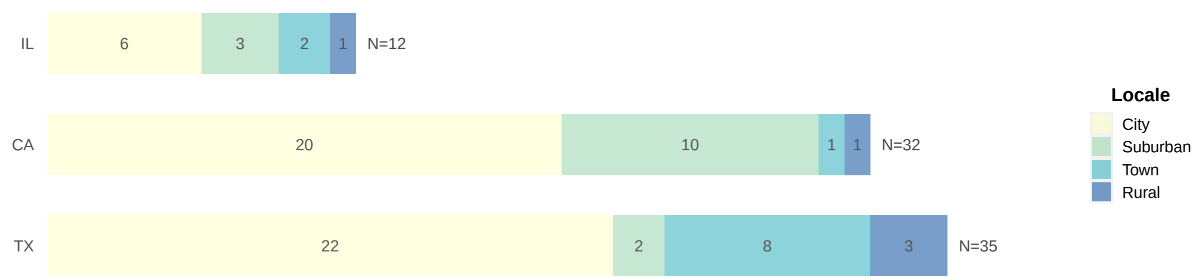


Figure A4: Summary of orders purchased by type

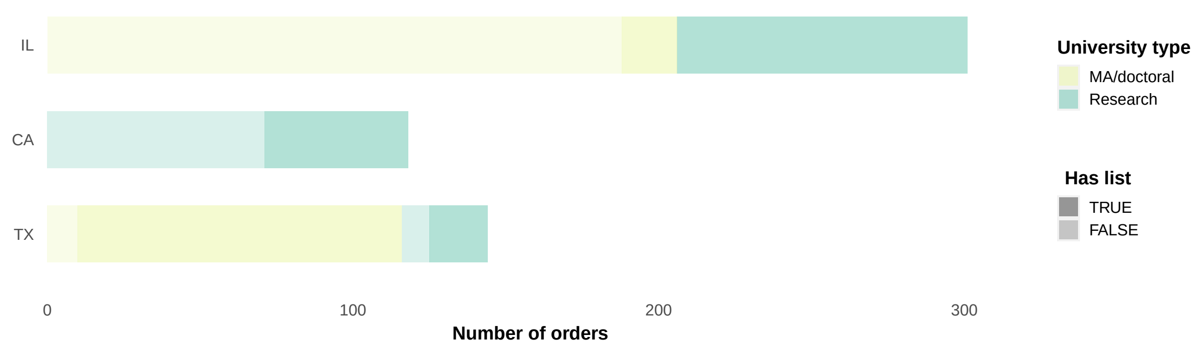


Figure A5: Summary of prospects by type

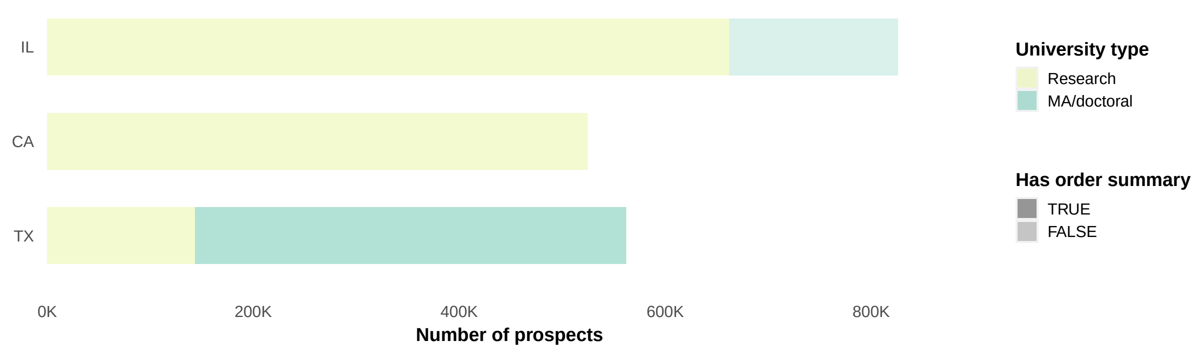
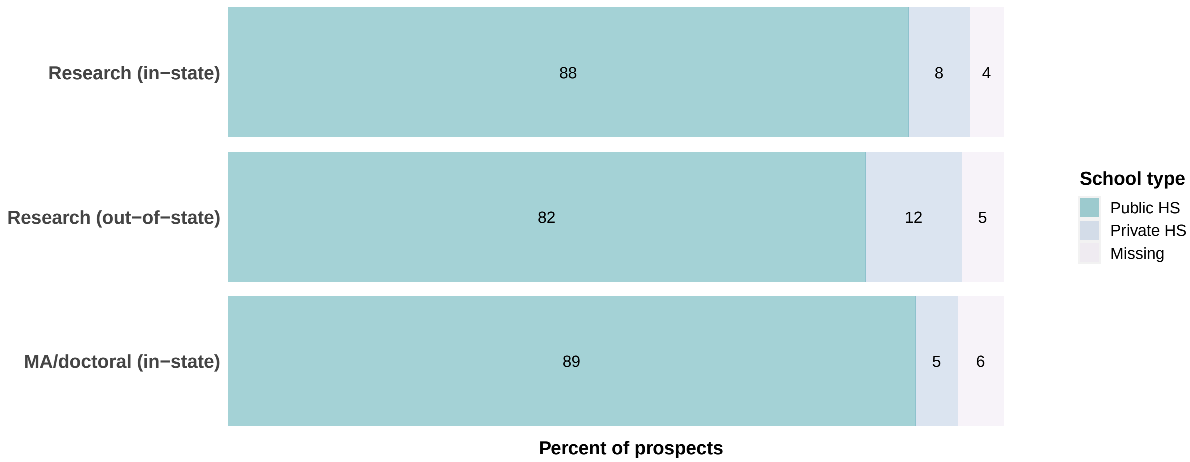


Figure A6: School type of prospects by research vs. ma/doctoral universities



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