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

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1 Introduction

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

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

Similar to the visual metaphor of the "STEM pipeline," the "enrollment funnel" – depicted in in Figure 1 – is a conceptual model used in the enrollment management industry to describes stages in the process of recruiting students. The funnel begins with a large pool of "prospects" that the university would like to "convert" into customers. The funnel narrows at each successive stage – inquiries, applicants, admits – in order to convey the assumption of "melt" (e.g., a subset of "inquiries" will apply), ending with the cohort of enrolled students. Practically, the enrollment funnel informs interventions that increase the probability of "conversion" from one stage to another (Campbell, 2017). For example, emails and brochures encourage prospects and inquiries to apply. Financial aid packages – institutional grant aid and loan guidance – convert admits to enrolled students.

Figure 1: The enrollment funnel

At the top of the enrollment funnel, universities identify leads by buying "student lists." Sometimes referred to as "names," student lists are the fundamental input for recruiting interventions that target individual prospects via mail, email, text, and on social media. The two dominant student list vendors are the College Board and ACT, which create student list products based on their database of standardized test takers. In fall 2021, the College Board Search and ACT Encoura student list products both charged \$0.50 per name (The College Board, 2021a). These products enable universities to control which prospects they purchase through the use of search filters (e.g., test score range, high school GPA range, zip code).

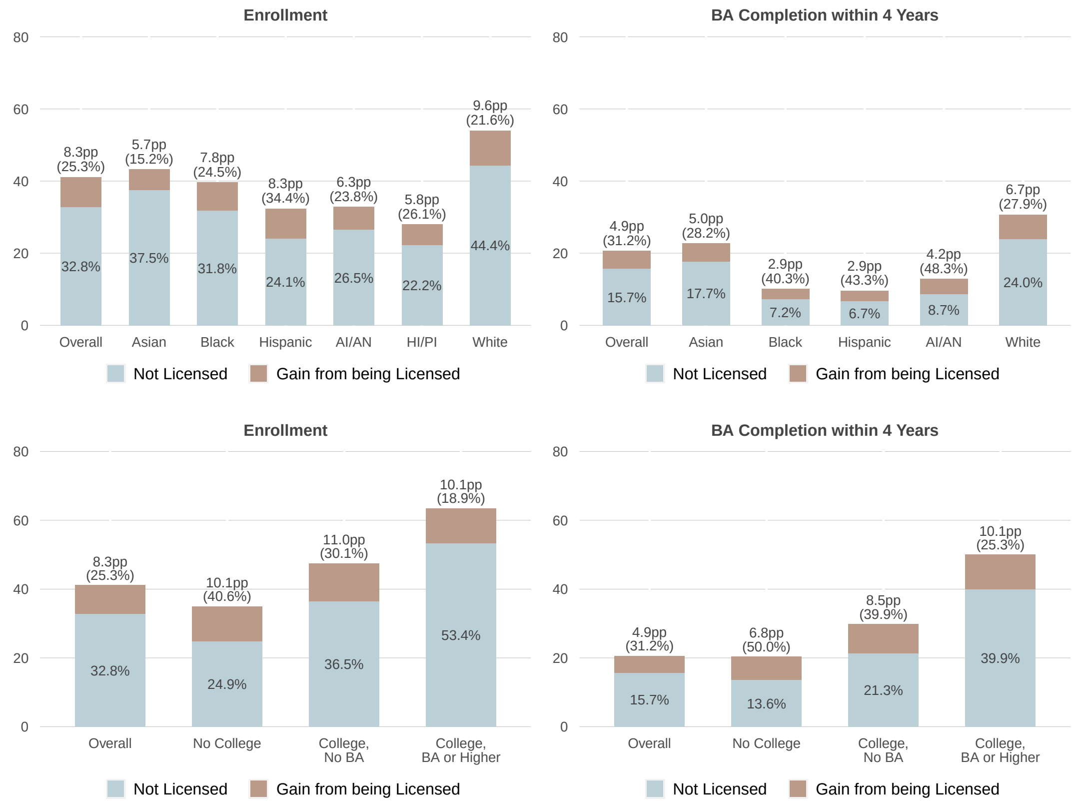
Student lists and student outcomes. Research suggests that student lists substantially affect college access outcomes – and in turn degree completion outcomes – for millions of students each year. Howell, Hurwitz, Mabel, & Smith (2021) compared SAT test-takers who opted into the College Board Student Search Service – allowing accredited institutions to "licence" their contact information – and test-takers who opted out, after controlling for covariates. Figure 2 reproduces the main results. For students with the same values of SAT score, parental education, race/ethnicity, sex, high school graduation year, and who attended the same high school, 41.1% of students who participated in Search attended a 4-year college compared to 32.8% of students who opted out, representing an 8.3 (`=41.1-32.8`) percentage point difference and a 25.3 (`=(41.1-32.8)/32.8`) percent change in the relative probability of attending a 4-year college (for a similar analysis of ACT's Educational Opportunity Service (EOS) see Moore (2017)).

Figure 2 shows that participating in Search was associated with a larger percent change in the probability of attending a 4-year institution for students who identified as Black (24.5%`=(39.6-31.8)/31.8`), Latinx (34.4%), American Indian or Alaska Native (23.8%), and Native Hawaiian or Pacific Islander (26.1%) than it was for students who identified as White (21.6%) or Asian (15.2%). Similarly, the percent change in the probability of attending a four-year college was higher for students whose parents did not attend college (40.6%) than it was for students whose parents had a BA (18.9%).

Given that the probability of graduating is affected by which institution a student attends (e.g., **???**; **???**), student lists may also affect degree completion through their effect on initial postsecondary institution. Howell et al. (2021) analyzed the four-year BA degree completion rates of SAT test-takers from the 2015 and 2016 high school graduation cohorts. Figure 2 shows that 20.6% of students who participated in Search obtained a BA in four years compared to 15.7% of students who opted out, representing a 31.2% (`=(20.6-15.7)/15.7`) increase in the relative probability of graduation. Furthermore, the relative increase in the probability of obtaining a BA was higher for Black (40.3%), Hispanic (43.3%), and Native American/Alaska Native students (48.3%) than it was for White (27.9%) and Asian (28.2%) students. The relative increase was also higher for students whose parents did not attend college (50.0%) than it was for students whose parents had a BA (25.3%).

Policy concerns. Given that student lists profoundly affect student outcomes, the policy concerns are which students are being excluded from the underlying student list databases and which students are being excluded from student list purchases. We argue that these policy concerns are primarily about student list products rather than how customers (universities) use these products.

Figure 2: Effects of College Board Student Search Service



Note: AI/AN = American Indian or Alaska Native. HI/PI = Hawaiian or Pacific Islander. The sample for enrollment outcomes includes all SAT takers in the 2015–2018 high school graduation cohorts. The sample for completion outcomes is restricted to students in the 2015–2016 cohorts. Completion results are not reported for HI/PI students due to very small sample size (N=2,749), which returns imprecise estimates. Results are estimated from regressions that include student-level controls for: sex, race/ethnicity, SAT score, parental education level, last Student Search Service opt-in status, and graduation cohort and high school fixed effects. All differences between students whose names were licensed and those whose names were not licensed are statistically significant at the 1% level.

Student list products exclude students in two ways. First, universities cannot purchase the contact information of prospects who are not included in the underlying database. While students who opt out of College Board Student Search Service are making a conscious decision, students cannot opt in unless they take a College Board Assessment (PSAT, SAT, AP). College Board and ACT assessments have been criticized for racial and socioeconomic bias (Dixon-Román, Everson, & Mcardle, 2013; Freedle, 2003; Hedges, 1998; Smith & Reeves, 2020; Walpole, McDonough, & Bauer, 2005). Test-taking rates differ substantially across race and class (Hyman, 2017), leading to systematic racial and socioeconomic inequality in which prospective students are included in the underlying databases that College Board and ACT student list products pull from. About 1.5 million students from the high school class of 2021 took the SAT compared to about 2.2 million students from the high school class of 2020 (The

College Board, 2021b) and about 1.3 million student from the high school class of 2021 took the ACT compared to about 1.7 million students from the high school class of 2020. These declines were driven by the Covid Pandemic and by the growth in test-optional and test-blind admissions policies. To the extent that student lists are an important mechanism for college access, the test-optional movement may have the unintended consequence of creating a college access crisis, in which the long-term decline in test-takers leads to fewer prospective students included in College Board/ACT student list databases which causes college access to decline.

Second, student list products exclude students by creating filters that enable universities to purchase some names but not others. While universities choose filters based on their preferences, these choices are structured by what the product allows. We are concerned that several commonly used filters systematically exclude protected classes and other populations that are underrepresented in higher education (e.g., rural students). For example, College Board and ACT student list products enable universities to filter prospects by zip code, which is highly correlated with race. College Board allows universities to target prospects based on their score in some set of AP exams, but which students attend high schools with widespread access to AP classes? An emerging trend is the creation of "geodemographic" filters that enable universities to select prospects based on the past behavior of students from their high school or neighborhood (e.g., how many students from this school attended an out-of-state university?) (The College Board, 2011, 2021a). Student list products enable universities to explicitly search for underrepresented groups (e.g., by race/ethnicity), but when used in conjunction with additional filters (e.g., test score range, high school characteristics) these searches tend to target more privileged members of the group.

While research sanctioned by College Board and ACT highlights the positive relationship between opting into student list products and college access (Howell et al., 2021; Moore, 2017; Smith, Howell, & Hurwitz, 2021), prior research has not examined which filter criteria universities select when purchasing student lists, what are the characteristics of purchased prospects, or the relationship between filter criteria and student characteristics. we collected data about student list purchases by issuing public records requests to public universities in five states. This report focuses on student lists purchased from College Board and addresses three research questions:

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

purchased prospects?

Due to data collection challenges, our analysis sample cannot be considered a random sample. Nevertheless, this research is an important first step towards developing a body of empirical research that informs policy discourse about regulating the student list business.

2 Data Collection and Research Design

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

2.1 Data Collection

Data collection sample. In 2019 we received funding from the Joyce Foundation and the Kresge Foundation for a research project that would utilize public records requests to collect data about recruiting behavior from all public universities in four states, California, Illinois, Minnesota, and Texas. Broadly, we sought two types of data: off-campus recruiting visits (e.g., visit from a university admissions representative to a local high school) and student list purchases.

IL and MN are focus states for the Joyce Foundation, while CA and TX are focus states for Kresge. The IL higher education system includes 3 universities in the University of Illinois system, 7 in the Illinois State University system, and 2 in the Southern Illinois University system. In MN, there are 5 universities in the University of Minnesota system and 7 in the Minnesota State University system. In CA, there are 9 universities in the University of California system and 23 in the California State University system. In TX, there are 8 universities in the University of Texas system, 4 in the Texas State University system, 11 in the Texas A&M University system, 4 in the University of Houston system, 2 in the University of North Texas system, 2 in the Texas Tech University system, and 4 independent Texas universities. We also collected data from Arizona State University and Northern Arizona University.

Table 1 and Figures 3 and 4 describe the public universities in our data collection sample. A majority of the universities are master's or doctoral universities and located in urban areas.

Public records requests. In late 2019, we signed an agreement with the Lawyers' Committee for Civil Rights Under Law (LCCR) to partner with us on the public records request

Table 1: University characteristics

State	System	University	Carnegie	25th pctl SAT/ACT	75th pctl SAT/ACT	In-state tuition	Out-of-state tuition	# Freshmen	% Out-of-state freshmen	% Pell	% White	% Black	% Latinx	% Asian/PI	% Non-resident alien
IL	U of IL	University of Illinois at Springfield	Master's Colleges & Universities: Larger Programs	947	1,188	$11,754.39	$18,588.71	300	9.7%	38.0%	55.0%	20.7%	16.0%	1.7%	4.3%
		University of Illinois at Chicago	Doctoral Universities: Highest Research Activity	990	1,221	$15,101.54	$25,614.16	3,307	7.6%	59.0%	24.8%	8.9%	38.5%	21.9%	2.8%
		University of Illinois at Urbana-Champaign	Doctoral Universities: Highest Research Activity	1,209	1,432	$17,562.60	$34,760.32	7,592	25.7%	23.6%	43.8%	7.2%	12.3%	19.6%	13.7%
	IL State U	Chicago State University	Master's Colleges & Universities: Medium Programs	795	971	$10,477.87	$17,591.21	86	26.7%	72.4%	15.1%	62.8%	1.2%	1.2%	5.8%
		Eastern Illinois University	Master's Colleges & Universities: Larger Programs	870	1,110	$11,705.33	$16,071.45	772	12.6%	51.2%	53.6%	27.5%	10.6%	1.0%	2.7%
		Governors State University	Master's Colleges & Universities: Larger Programs	830	990	$10,747.69	$19,087.47	218	1.8%	69.7%	18.3%	64.2%	9.6%	0.5%	0.5%
		Northeastern Illinois University	Master's Colleges & Universities: Larger Programs	790	950	$ 9,414.96	$17,036.25	801	1.6%	63.8%	17.2%	21.2%	43.1%	9.7%	4.0%
		Western Illinois University	Master's Colleges & Universities: Larger Programs	870	1,070	$12,654.80	$17,047.49	1,527	6.8%	54.5%	43.9%	34.6%	14.7%	0.7%	0.9%
		Illinois State University	Doctoral Universities: Higher Research Activity	990	1,190	$12,277.67	$17,003.54	3,694	3.6%	30.3%	71.0%	10.9%	12.2%	2.1%	0.5%
		Northern Illinois University	Doctoral Universities: Higher Research Activity	910	1,149	$14,362.61	$24,191.49	1,802	5.0%	45.6%	46.7%	24.5%	18.0%	4.7%	1.1%
	SIU	Southern Illinois University-Edwardsville	Master's Colleges & Universities: Larger Programs	949	1,188	$10,011.82	$11,440.62	1,935	15.3%	34.4%	70.5%	15.2%	4.9%	2.5%	0.4%
		Southern Illinois University-Carbondale	Doctoral Universities: Higher Research Activity	909	1,149	$13,361.02	$26,685.25	1,693	15.4%	45.9%	58.4%	23.1%	11.5%	1.1%	1.3%
MN	UMN	University of Minnesota-Rochester	Special Focus Four-Year: Other Health Professions Schools	1,028	1,217	$13,523.53	$13,523.53	145	24.8%	37.2%	62.8%	9.7%	5.5%	18.6%	0.7%
		University of Minnesota-Crookston	Baccalaureate Colleges: Diverse Fields	943	1,110	$11,957.77	$11,957.77	209	34.0%	33.8%	75.6%	6.2%	3.3%	1.0%	5.3%
		University of Minnesota-Morris	Baccalaureate Colleges: Arts & Sciences Focus	1,029	1,261	$13,129.02	$15,173.08	376	16.2%	34.7%	64.9%	2.1%	5.9%	2.4%	3.7%
		University of Minnesota-Duluth	Master's Colleges & Universities: Larger Programs	1,029	1,190	$13,428.48	$17,870.23	2,138	15.3%	23.1%	83.7%	2.4%	3.5%	4.3%	1.4%
		University of Minnesota-Twin Cities	Doctoral Universities: Highest Research Activity	1,189	1,387	$14,453.57	$24,330.49	5,880	35.7%	18.0%	71.1%	3.4%	3.8%	10.8%	5.8%
	MN State U	Bemidji State University	Master's Colleges & Universities: Small Programs	950	1,110	$ 8,578.94	$ 8,578.94	814	12.9%	32.7%	84.4%	1.4%	2.7%	0.9%	2.5%
		Minnesota State University Moorhead	Master's Colleges & Universities: Medium Programs	949	1,149	$ 8,292.77	$15,585.99	870	30.8%	28.6%	77.7%	1.8%	4.4%	0.8%	8.9%
		Southwest Minnesota State University	Master's Colleges & Universities: Medium Programs	864	1,070	$ 8,530.90	$ 8,530.90	491	27.3%	37.6%	64.0%	8.1%	4.3%	2.6%	13.8%
		Winona State University	Master's Colleges & Universities: Medium Programs	948	1,149	$ 9,274.94	$15,097.45	1,575	37.1%	26.0%	85.7%	2.4%	4.1%	2.5%	1.5%
		Metropolitan State University	Master's Colleges & Universities: Larger Programs			$ 7,732.69	$14,711.13	134	3.0%	76.2%	22.4%	26.1%	6.0%	37.3%	7.5%
		Minnesota State University-Mankato	Master's Colleges & Universities: Larger Programs	948	1,110	$ 8,031.13	$15,945.74	2,433	16.9%	27.6%	75.8%	4.4%	5.1%	3.8%	5.6%
		Saint Cloud State University	Master's Colleges & Universities: Larger Programs	871	1,111	$ 8,084.27	$16,176.72	1,782	13.9%	36.4%	65.2%	6.8%	4.8%	8.4%	10.4%
CA	UC	University of California-Merced	Doctoral Universities: Higher Research Activity	885	1,085	$13,554.19	$40,824.04	2,048	0.2%	66.4%	9.4%	5.3%	55.3%	18.9%	7.8%
		University of California-Berkeley	Doctoral Universities: Highest Research Activity	1,316	1,527	$13,806.63	$41,076.48	6,252	24.4%	19.4%	25.6%	1.8%	13.8%	42.7%	9.3%
		University of California-Davis	Doctoral Universities: Highest Research Activity	1,088	1,349	$14,355.46	$41,625.31	5,762	19.4%	33.3%	23.9%	1.9%	23.4%	28.0%	16.4%
		University of California-Irvine	Doctoral Universities: Highest Research Activity	1,078	1,334	$13,654.34	$40,924.20	6,551	25.8%	37.8%	11.1%	1.8%	26.2%	33.9%	21.7%
		University of California-Los Angeles	Doctoral Universities: Highest Research Activity	1,202	1,466	$13,204.65	$40,474.50	6,545	25.0%	29.9%	25.0%	3.4%	23.4%	28.6%	11.1%
		University of California-Riverside	Doctoral Universities: Highest Research Activity	956	1,200	$13,880.21	$41,150.07	5,358	2.2%	56.6%	10.1%	4.0%	47.2%	31.1%	2.5%
		University of California-San Diego	Doctoral Universities: Highest Research Activity	1,193	1,455	$13,945.62	$41,215.48	5,748	26.5%	30.7%	15.5%	1.5%	20.6%	34.4%	21.6%
		University of California-Santa Barbara	Doctoral Universities: Highest Research Activity	1,161	1,402	$14,383.05	$41,652.91	4,996	15.0%	33.3%	31.8%	1.7%	25.6%	18.9%	10.9%
		University of California-Santa Cruz	Doctoral Universities: Highest Research Activity	1,094	1,309	$13,837.29	$41,107.14	4,221	8.5%	32.3%	31.2%	1.9%	25.6%	24.2%	6.3%
	CSU	California State University Maritime Academy	Baccalaureate Colleges: Diverse Fields			$ 6,957.99	$18,363.87	241	16.6%	27.1%	37.8%	1.7%	26.1%	11.6%	0.8%
		California State University-Channel Islands	Master's Colleges & Universities: Small Programs			$ 6,691.24	$18,097.12	1,010	0.5%	52.0%	21.5%	3.1%	55.6%	4.6%	2.4%
		California State University-Monterey Bay	Master's Colleges & Universities: Medium Programs			$ 6,519.54	$17,925.42	802	5.6%	56.6%	20.2%	4.5%	57.1%	5.9%	3.7%
		California State University-San Marcos	Master's Colleges & Universities: Medium Programs	863	1,063	$ 7,545.66	$18,951.54	2,152	4.0%	45.4%	25.5%	2.6%	47.7%	9.8%	5.0%
		Humboldt State University	Master's Colleges & Universities: Medium Programs	870	1,096	$ 7,367.83	$18,773.70	1,295	6.9%	52.7%	36.1%	3.9%	42.4%	2.7%	1.4%
		California Polytechnic State University-San Luis Obispo	Master's Colleges & Universities: Larger Programs	1,170	1,370	$ 9,274.94	$20,680.81	4,341	16.7%	13.8%	56.6%	0.6%	15.0%	13.6%	1.5%
		California State Polytechnic University-Pomona	Master's Colleges & Universities: Larger Programs	913	1,176	$ 7,222.70	$18,628.57	4,204	4.0%	44.3%	14.7%	4.3%	46.2%	21.5%	6.4%
		California State University-Bakersfield	Master's Colleges & Universities: Larger Programs			$ 7,008.07	$18,413.95	1,362	2.9%	65.9%	12.7%	6.3%	64.8%	6.5%	5.1%
		California State University-Chico	Master's Colleges & Universities: Larger Programs	890	1,103	$ 7,195.10	$18,600.98	2,762	1.8%	44.0%	38.7%	3.3%	38.2%	5.5%	2.6%
		California State University-Dominguez Hills	Master's Colleges & Universities: Larger Programs			$ 6,564.51	$17,970.38	1,299	0.5%	68.3%	2.1%	11.5%	71.3%	6.8%	5.0%
		California State University-East Bay	Master's Colleges & Universities: Larger Programs			$ 6,708.62	$18,114.49	1,596	4.4%	53.7%	8.0%	11.0%	46.7%	19.6%	6.6%
		California State University-Long Beach	Master's Colleges & Universities: Larger Programs	936	1,169	$ 6,602.33	$18,008.20	4,253	4.3%	48.8%	16.6%	4.4%	41.3%	24.2%	4.7%
		California State University-Los Angeles	Master's Colleges & Universities: Larger Programs	769	972	$ 6,523.63	$17,929.50	3,830	1.8%	70.4%	2.9%	4.1%	71.0%	11.7%	7.0%
		California State University-Northridge	Master's Colleges & Universities: Larger Programs	798	1,039	$ 6,732.12	$18,138.00	4,499	3.5%	61.6%	13.9%	6.4%	56.4%	9.9%	7.2%
		California State University-Sacramento	Master's Colleges & Universities: Larger Programs	830	1,045	$ 7,052.02	$18,457.89	3,760	1.8%	54.5%	18.3%	6.8%	37.8%	22.4%	3.5%
		California State University-San Bernardino	Master's Colleges & Universities: Larger Programs	783	971	$ 6,755.63	$18,161.51	2,791	2.0%	67.6%	7.4%	5.8%	71.0%	4.3%	6.5%
		California State University-Stanislaus	Master's Colleges & Universities: Larger Programs			$ 6,876.23	$18,282.11	1,389	0.6%	61.6%	17.6%	1.9%	56.9%	10.4%	4.8%
		San Jose State University	Master's Colleges & Universities: Larger Programs	929	1,150	$ 7,581.43	$18,987.31	3,208	5.6%	39.8%	14.1%	4.1%	31.9%	34.2%	7.0%
		Sonoma State University	Master's Colleges & Universities: Larger Programs	890	1,090	$ 7,550.77	$18,956.65	1,806	1.5%	32.9%	41.8%	2.4%	36.4%	5.4%	2.3%
		California State University-Fresno	Doctoral Universities: Moderate Research Activity	797	1,016	$ 6,452.09	$17,857.96	3,302	2.7%	63.4%	15.3%	3.0%	54.9%	14.7%	5.3%
		California State University-Fullerton	Doctoral Universities: Moderate Research Activity	917	1,117	$ 6,704.53	$18,110.40	4,426	5.1%	46.9%	14.4%	2.2%	48.7%	19.9%	7.2%
		San Francisco State University	Doctoral Universities: Moderate Research Activity	863	1,095	$ 6,626.85	$18,032.73	3,642	3.5%	46.2%	17.2%	4.5%	37.8%	25.1%	6.2%
		San Diego State University	Doctoral Universities: Higher Research Activity	1,028	1,236	$ 7,240.07	$18,645.95	5,077	20.4%	23.8%	36.9%	4.2%	27.0%	13.4%	6.8%
TX	U of TX	The University of Texas of the Permian Basin	Master's Colleges & Universities: Medium Programs	858	1,048	$ 5,901.21	$ 7,111.30	496	6.2%	41.0%	18.1%	3.2%	71.8%	1.2%	3.0%
		The University of Texas at Tyler	Master's Colleges & Universities: Larger Programs	950	1,150	$ 7,718.38	$20,473.34	825	3.9%	31.9%	55.5%	8.0%	17.0%	3.9%	1.0%
		The University of Texas Rio Grande Valley	Doctoral Universities: Moderate Research Activity	862	1,038	$ 7,601.87	$17,609.61	3,944	2.5%	68.9%	2.0%	0.5%	92.7%	1.6%	1.7%
		The University of Texas at El Paso	Doctoral Universities: Higher Research Activity	824	1,030	$ 7,509.89	$20,770.75	3,442	7.7%	62.2%	3.9%	2.8%	86.2%	0.9%	4.5%
		The University of Texas at San Antonio	Doctoral Universities: Higher Research Activity	930	1,137	$ 7,869.65	$18,700.12	4,377	3.5%	44.9%	21.7%	10.2%	53.9%	7.9%	1.7%
		The University of Texas at Arlington	Doctoral Universities: Highest Research Activity	950	1,190	$ 9,827.86	$23,424.97	3,054	7.6%	43.2%	30.0%	9.8%	32.3%	15.0%	6.2%
		The University of Texas at Austin	Doctoral Universities: Highest Research Activity	1,163	1,415	$10,314.34	$36,468.14	8,719	12.2%	22.8%	39.4%	4.4%	23.8%	22.3%	5.2%
		The University of Texas at Dallas	Doctoral Universities: Highest Research Activity	1,144	1,380	$11,438.58	$29,442.69	3,229	7.5%	24.3%	31.5%	4.4%	15.6%	36.6%	4.7%
	TX State U	Sul Ross State University	Master's Colleges & Universities: Larger Programs	760	949	$ 6,560.42	$16,568.16	351	4.3%	60.9%	28.5%	15.1%	54.7%	0.3%	0.0%
		Lamar University	Doctoral Universities: Moderate Research Activity	863	1,056	$ 8,325.47	$18,333.21	2,301	2.5%	46.6%	46.0%	28.2%	17.7%	4.5%	0.7%
		Sam Houston State University	Doctoral Universities: Moderate Research Activity	886	1,086	$ 7,933.01	$17,940.75	2,758	2.6%	48.0%	42.8%	22.7%	28.9%	2.1%	0.6%
		Texas State University	Doctoral Universities: Higher Research Activity	936	1,130	$ 9,816.62	$21,492.31	5,732	2.0%	37.6%	43.0%	11.3%	39.4%	2.2%	0.3%
	TX A&M	Texas A&M University-Texarkana	Master's Colleges & Universities: Medium Programs	961	1,070	$ 6,990.70	$18,280.06	205	15.6%	42.2%	46.3%	12.7%	24.4%	5.9%	1.0%
		Tarleton State University	Master's Colleges & Universities: Larger Programs	859	1,059	$ 7,297.31	$17,096.55	2,169	1.8%	39.8%	65.5%	8.4%	20.7%	0.6%	0.0%
		Texas A & M International University	Master's Colleges & Universities: Larger Programs	811	1,011	$ 7,170.58	$17,319.35	1,113	1.7%	67.1%	1.4%	0.3%	95.8%	0.5%	1.2%
		Texas A & M University-Central Texas	Master's Colleges & Universities: Larger Programs			$ 6,397.92	$17,243.72								
		West Texas A & M University	Master's Colleges & Universities: Larger Programs	862	1,091	$ 7,608.00	$ 8,748.59	1,330	14.2%	35.6%	59.2%	5.6%	28.0%	1.5%	0.9%
		Prairie View A & M University	Doctoral Universities: Moderate Research Activity	746	929	$10,280.62	$23,893.06	1,839	6.8%	69.4%	1.1%	87.1%	7.9%	1.0%	0.5%
		Texas A & M University-Corpus Christi	Doctoral Universities: Moderate Research Activity	842	1,064	$ 8,609.60	$18,659.23	2,410	3.2%	43.3%	34.5%	8.7%	49.0%	2.5%	1.6%
		Texas A & M University-Kingsville	Doctoral Universities: Moderate Research Activity	839	1,066	$ 8,226.33	$21,825.49	1,257	1.3%	55.2%	17.3%	6.9%	72.3%	1.2%	1.0%
		Texas A & M University-Commerce	Doctoral Universities: Higher Research Activity	870	1,075	$ 7,920.75	$20,430.42	1,004	2.3%	55.2%	32.1%	29.6%	24.8%	1.8%	0.6%
		Texas A & M University-College Station	Doctoral Universities: Highest Research Activity	1,087	1,323	$10,355.23	$29,622.57	10,145	6.2%	20.6%	60.1%	3.6%	24.0%	7.7%	1.1%
		Texas A&M University-San Antonio	Unknown	755	965	$ 6,459.24	$16,334.11	492	1.6%	63.8%	30.3%	16.5%	37.8%	4.3%	3.5%
	U of Houston	University of Houston-Downtown	Master's Colleges & Universities: Small Programs	822	990	$ 6,141.39	$15,835.36	939	1.5%	60.7%	3.6%	8.9%	70.0%	8.2%	7.2%
		University of Houston-Clear Lake	Master's Colleges & Universities: Larger Programs	935	1,099	$ 6,645.25	$18,958.69	266	0.0%	38.3%	35.0%	6.4%	42.1%	10.9%	2.3%
		University of Houston-Victoria	Master's Colleges & Universities: Larger Programs			$ 6,128.10	$16,135.84	319	2.5%	65.2%	19.7%	22.3%	50.8%	2.2%	0.9%
		University of Houston	Doctoral Universities: Highest Research Activity	1,050	1,253	$ 9,728.72	$22,189.33	4,463	6.6%	36.8%	23.1%	9.7%	32.2%	26.3%	3.6%
	UNT	University of North Texas at Dallas	Master's Colleges & Universities: Small Programs	830	1,005	$ 7,715.32	$17,723.05	280	1.1%	70.7%	5.4%	13.6%	75.0%	2.9%	1.8%
		University of North Texas	Doctoral Universities: Highest Research Activity	984	1,196	$10,376.69	$20,384.42	4,850	7.4%	37.2%	42.7%	13.3%	26.5%	8.1%	2.7%
	TX Tech	Angelo State University	Master's Colleges & Universities: Larger Programs	870	1,088	$ 7,202.26	$17,209.99	1,584	6.1%	47.2%	47.0%	9.9%	36.5%	0.7%	2.2%
		Texas Tech University	Doctoral Universities: Highest Research Activity	1,025	1,210	$ 8,613.68	$18,621.42	4,762	8.3%	24.3%	60.4%	5.8%	24.9%	3.1%	3.7%
	Indy TX	Midwestern State University	Master's Colleges & Universities: Medium Programs	870	1,075	$ 8,476.73	$10,469.69	740	6.8%	46.6%	51.2%	15.4%	22.6%	2.4%	1.5%
		Stephen F Austin State University	Master's Colleges & Universities: Larger Programs	887	1,099	$ 7,886.00	$17,893.73	2,371	1.3%	40.8%	54.8%	18.6%	20.4%	1.4%	0.5%
		Texas Southern University	Doctoral Universities: Moderate Research Activity	724	904	$ 8,662.74	$21,707.96	1,260	16.4%	75.6%	2.7%	86.7%	5.2%	1.4%	2.5%
		Texas Woman's University	Doctoral Universities: Moderate Research Activity	830	1,057	$ 7,483.32	$17,491.05	1,302	3.5%	51.0%	25.6%	21.6%	39.6%	11.4%	0.4%

Figure 3: University by carnegie classification

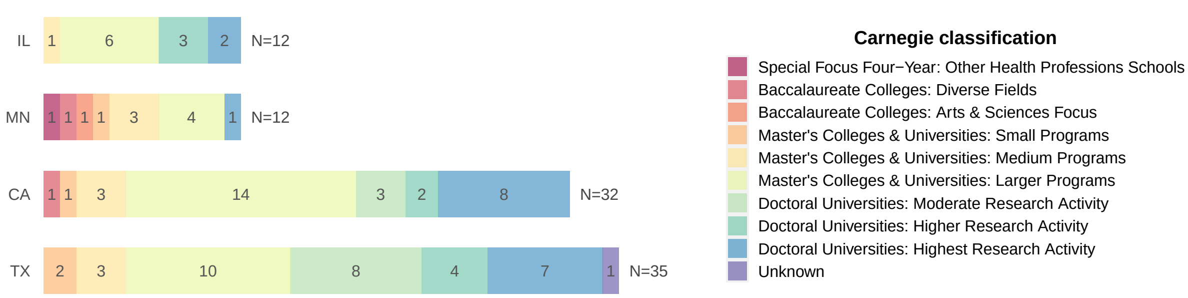
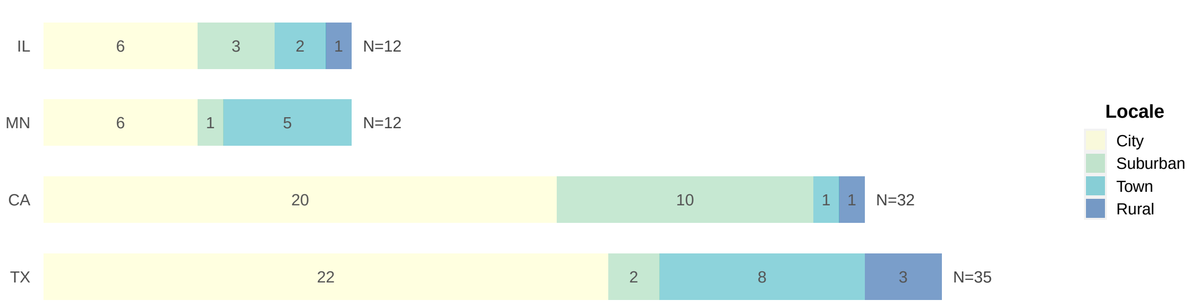


Figure 4: University by locale



data collection. LCCR was created by the Kennedy Administration to leverage private sector legal expertise towards civil rights. LCCR typically operates by connecting projects with the pro bono efforts of corporate law firms. LCCR recruited firms to work on our project. Unfortunately, several firms that expressed initial interest withdrew following conflict of interest checks. However, LCCR generously allocated time of an internal staff attorney towards our project. Additionally, one firm offered to help us collect data from Arizona public universities. Although Arizona was not part of the funded project, we gratefully accepted.

We began issuing public records requests in February 2020, following several months of planning and pilot requests. We issued one records request letter for each public university. An example records request letter can be found here. Each request letter asked for data about off-campus recruiting visits and student list purchases for the purpose of undergraduate recruiting, which were made from August 2016 to the present. For each student list purchase from a student list vendor, we requested two related pieces of data: the order summary, which specifies search criteria for the student list purchase; and the de-identified prospect-level list produced from the search criteria.

As such, we conceived of our data collection as requesting three types of information: (1) off-campus recruiting visits; (2) student list order summaries; and (3) de-identified student list data. Each request letter included examples of desired off-campus recruiting visit data, student list order summary data, and de-identified student list data as attachments.

Data collection challenges and successes. Appendix figures summarize the success to date of our data collection efforts and report the status of data collection for each university. We received usable quantitative off-campus recruiting visit data from X universities, usable student list order summary data from X universities, and usable de-identified student list data from X universities.

Using public records requests to collect quantifiable data is difficult under the best of circumstances. Unfortunately, we started collecting data just as COVID-19 emerged. Several additional challenges – some foreseeable and tractable and others not – made data collection difficult. State public records request laws generally require public entities to redact records that contain sensitive personal information but do not require public entities to create new records. Consider a prospect-level student list stored by a public university in a spreadsheet format. Removing personally identifiable information (e.g., fields for name, mailing address, email address) is part of the redaction process. By contrast, if information about off-campus recruiting visits stored in old emails or an antiquated calendar system, compiling these records would be considered creating new records rather than redaction. This turned out to be the most common reason we did not obtain off-campus recruiting visit data.

For student list purchases, an additional complication is that universities may purchase lists from multiple vendors. When we initiated data collection, the three largest vendors were College Board, ACT, and the National Research Center for College and University Admissions (NRCCUA), which had just been purchased by NRCCUA. In subsequent communication with universities, we narrowed our student list purchase requests to these three vendors.

Many public universities outsourced student list purchases to an enrollment management consulting firm, which created several challenges. Employees at these universities often lacked knowledge about student list purchases and were unfamiliar with the records we requested. Employee turnover often exacerbated this lack of institutional knowledge. Enrollment management consulting firms posed another barrier. When lists were purchased by a consulting firm, the university often did not have the requested order summaries and/or student lists in their possession. Furthermore, the summary information firms regularly sent to universities was too aggregate for our analyses, but firms were unwilling to help provide the original records we sought.

In response to early data collection challenges, we created a "vendor portal document." This document provided detailed instructions – separately for College Board, ACT, and NRCCUA – for how to log-in to the online portal, obtain the order summary for each student list purchase, obtain student list data for each purchase, and how to de-identify these data. Unfortunately, this document was less effective for ACT and NRCCUA than it was for College Board. ACT released the Encoura platform in 2021, following its 2018 acquisition of NRCCUA. The online portals that provided access to students lists purchased from the legacy ACT and NRCCUA student list products were continued. Furthermore, whereas the College Board portal gave customers access to student lists purchased in the last X years, the Encoura portal provided access to purchases within the previous 12 months.

The most common data collection challenges were universities not replying to the request or denying the request. The legal grounds for these denials were often questionable. We learned that obtaining these data depends on treating each university as a protracted negotiation – often several negotiations – that requires sustained effort and some degree of leverage. Even with time from a LCCR staff attorney, we lacked sufficient capacity for sustained negotiations with each university and we lacked a stick that commanded university attention.

In Spring 2021, LCCR successfully recruited three law firms to represent data collection efforts in Illinois, Minnesota, and California, respectively. However, we were unable to obtain representation for Texas. The firms produced legal research that demonstrated the legitimacy of our requests and picked-apart denials based on questionable legal grounds (e.g,. “trade secrets”). Next, the firms systematically engaged universities, often directly engaging the university or system-level general counsel, who then directed the public records office and other offices to cooperate with our request. Firm representation substantially increased the number of successful requests. However, many universities provided legitimate reasons for not providing one or more requested data elements (e.g., records no longer exist, not required to create new records). Some universities denied request elements on grounds that firms believed lacked legal merit. However, we made a collective decision not pursue litigation.

In hindsight, we identify several changes may benefit efforts to collect public records in the enrollment management space. First, many universities were understandably overwhelmed by a request for several complicated, esoteric data sources. We could have issued several narrower requests rather than a single multi-aceted request. Related, our request for student list data should have proceeded in two stages: first, requesting contracts with a specific set of student list vendors over a time period; and, second, for each contract received, issuing a separate records request for the student list order summaries de-identified student lists associated with that contract. Third, we underestimated the extent to which university personnel were unfamiliar with student list purchases and also the number of universities that outsourced student list purchases to a consulting firm. We should have created the “vendor portal” instructions document at the beginning of the data collection process.

Data processing. Records received from universities were visually inspected to check whether they contained the requested fields and data structure. If not, we communicated the problems to the university and asked for revised records. Records that passed visual inspection were processed. The order summaries were generally provided as PDF files and were parsed using Python, a general-purpose programming language, and converted to tabular data. The student-level lists – typically received as csv or text files – were imported and cleaned using the statistical programming language R. If processing revealed additional problems with the data, we asked the university for revised records.

2.2 Research Design

Analysis sample. We decided to restrict this report to student lists purchased from College Board in order to avoid overwhelming the reader (and ourselves!). Future analyses will incorporate lists purchased from ACT and other vendors. Table 2 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. Preliminary results below are based on an analysis sample that consists of 13 universities that provided

Table 2: Summary of data received

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

some order summary and some student list data. Across these 13 universities, we received 503 order summaries that make up the analysis sample for our first research question. Of those 503 order summaries, we received 405 accompanying student lists that make up the analysis sample for research questions one and two.

To what extent are the student list purchases we analyze representative of student lists purchased by universities in our analysis sample? Universities may purchase student lists from several different vendors but College Board and ACT dominate the market. In CA and TX, the majority of test-takers take the SAT (The College Board, 2021c). Historically, most IL test-takers took the ACT, but in 2016 the state signed a contract with College Board for all IL juniors to take the SAT (The College Board, 2021d). In MN, the vast majority of test-takers take the ACT. These state-by-state differences suggest that students lists purchased from College Board will not be representative of all student lists purchases, particularly for MN public universities. Another issue is that some universities provide incomplete data about student lists purchased from College Board during the requested time period. When we received the order summary for a particular purchase but not the de-identified student list – or vice-versa – we have direct evidence of incomplete data. However, we usually cannot assess whether the data we received identifies the full set of student lists purchased from College Board.

Our inability to obtain data from all universities creates external validity concerns. An ideal analysis dataset includes all student lists purchased from College Board by all public universities in our data collection sample, or at least a random sample of these universities. Unfortunately, our analysis sample cannot be considered a random sample. Moreover, we suspect that non-response was systematically related to factors of substantive interest. For example, we were less successful obtaining records from universities that outsourced student list purchases to consulting firms. In turn, response bias affects external validity. Based on our results, we cannot make inferences about the population of universities in the four data collection states. Nor can we make inferences about the broader population of US public universities.

Research questions and analyses. Choices about research questions were informed by the limitations of our analysis sample and by substantive considerations. We cannot make

Table 3: Summary of orders and prospects purchased

# orders total	# orders with list	# prospects total	# prospects with order
503	288	2,123,563	1,959,837

Figure 5: Summary of orders purchased by carnegie classification

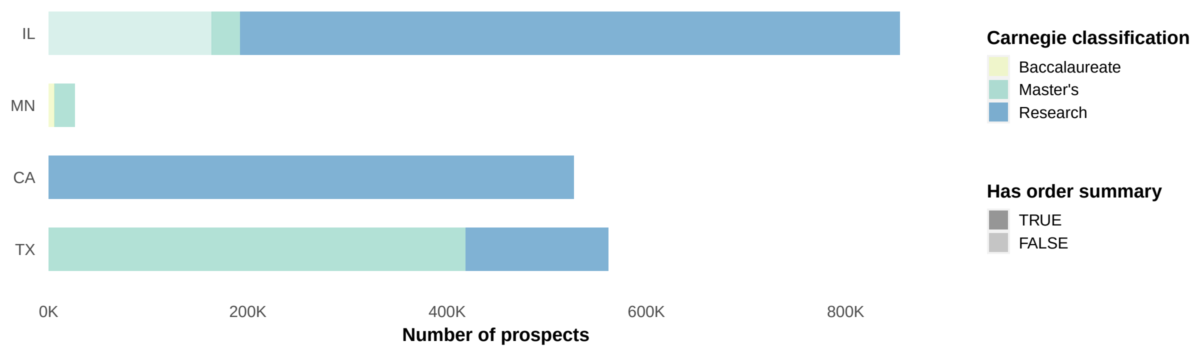
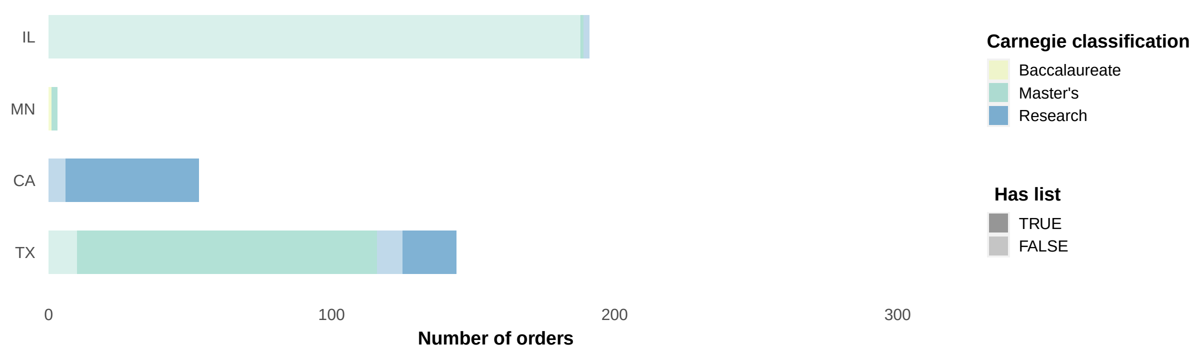


Figure 6: Summary of prospects purchased by carnegie classification



statements about university behavior that extends beyond our analysis sample. Assuming our data is representative of lists purchased by universities in our sample, we can make statements about the College Board student lists purchased by universities in our analysis sample. This reasoning suggests treating our sample as a multiple case study (Eisenhardt, 1989). The behaviors observed in our sample identify behaviors that exist in the population of public public universities, but not the prevalence of these behaviors in the population.

More substantively, during the course of data collection we realized that research should focus on the student list products themselves rather than the behavior of customers (universities) who buy the product. Systematic inequality in purchased versus excluded names is a function of (A) which prospective students are included in the underlying data base and (B) the set of filters that universities can utilize to select prospects and finally (C) university choices about which filters to select. Thus, while universities choose which filters to apply to each list purchase, these choices – and the resulting set of names – are structured by what the product allows. These considerations suggest analyses that investigate the relationship between the filters chosen for a particular student list purchase and who is included in the resulting student list.

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

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

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

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

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

3 Results

3.1 Characteristics of Student List Purchases

3.1.1 Total Orders and Number of Prospects

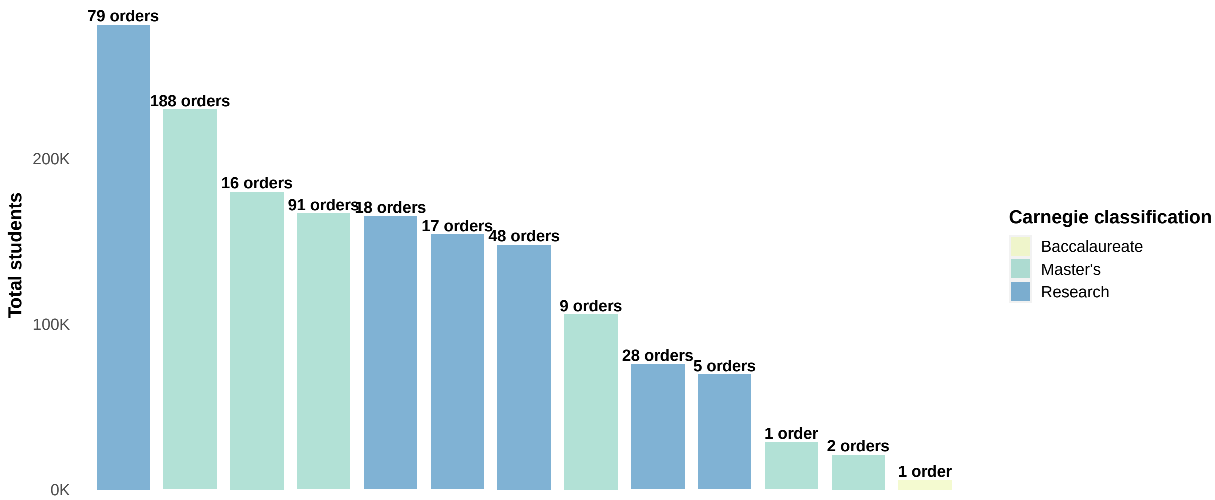
Figure 7 presents the 503 total orders analyzed in this report by university type and total students purchased. The 503 orders were purchased across 13 universities. The six master's universities in the study made the majority of order purchases (N=307), while research universities made 195 orders and the only baccalaureate university in the study made one order.

The number of total prospects purchased within each order varied widely. Across all 503 orders, the median number of prospects purchased per order was 998, whereas the mean was 3,272 (sd=6,119). Despite making fewer total orders than master's universities, research universities on average purchased nearly double the number of students per order (4,698 versus 2,382). The only baccalaureate college in the study purchased 5,539 prospects in their one College Board order.

3.1.2 Frequency of Filters Used

Filters used to select prospect lists varied across academic criteria (e.g., GPA, PSAT, SAT, academic rank, AP Score), geographic location (e.g., zip code, state, segment, core based statistical area, geomarket, international), and demographic characteristics (e.g., high school graduation class, race/ethnicity, gender). Some geographic filters are metrics created by the College Board. For example, segment filters come from the College Board's "Segment

Figure 7: Orders purchased by carnegie classification



Analysis Service" which merges demographic, geographic, and academic data on SAT test takers to create "geodemographic profiles" for college-bound students (The College Board, 2011, p. 3). These profiles are created at the neighborhood-level and at the school-level. Geomarket filters are also created by the College Board within Enrollment Management Services, which uses 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 high school graduates in the area [CITE].

Figure 8 shows how often filters were used across all orders. All 503 orders filtered by high school graduation class. The most frequently used filters include GPA (93%), PSAT scores (59%), SAT scores (57%), and zip code (55%). About two in every five orders also filtered by state. Only a subset of orders filtered by race/ethnicity (15%), academic rank (10%), gender (5%), segment (4%), AP score (4%), core based statistical area (3%), geomarket (3%), and international (3%).

[REFER TO TABLE FOR GPA; DON'T UNDERSTAND THE GPA TABLE; THERE SHOULD BE A FIGURE FOR SAT; THE TEXT ON SAT IN THIS PARAGRAPH IS TEDIUS TO FOLLOW] The three most commonly used academic filters (GPA, PSAT, SAT) were used by specifying a low and/or high threshold. Across the 469 orders using GPA, low thresholds ranged from A+ to C, with the majority of orders using a low of B- (50%) or C+ (19%). All orders using GPA orders indicated a high threshold of A+. For orders using PSAT lowest score thresholds, 30% indicated less than 1000, 18% indicated 1000-1100, 19% indicated 1110-1200, 17% indicated 1210-1300, 7% indicated 1310-1400, and 9% indicated 1410-1500. For orders using PSAT highest score thresholds, 13% indicated less than 1000, 12% indicated 1000-1100, 26% indicated 1110-1200, 19% indicated 1210-1300, 11% indicated

Figure 8: Filters used in order purchases

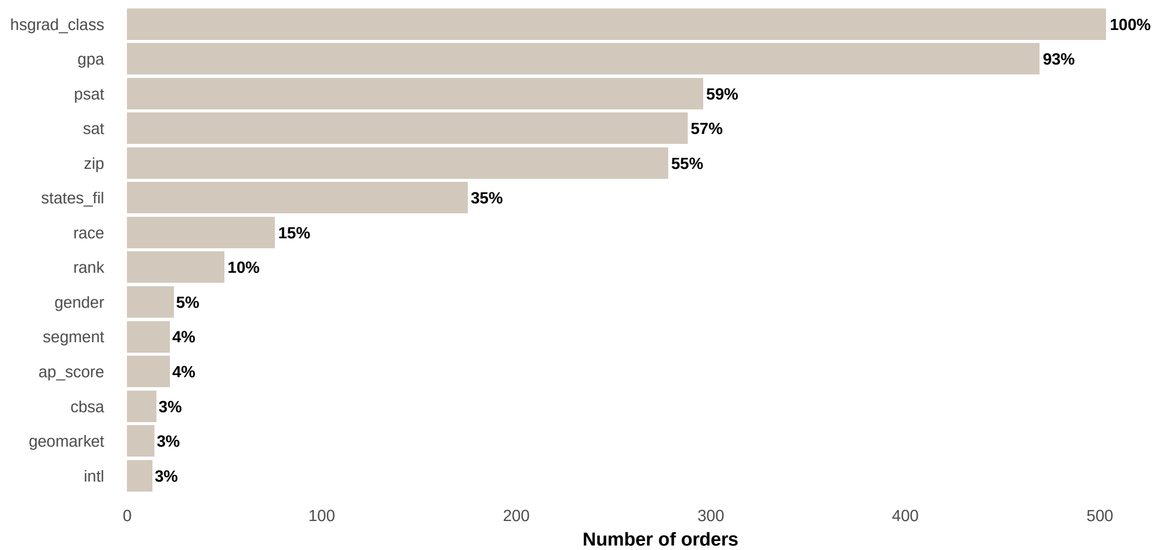


Table 4: Filter by GPA

GPA	# low	% low	# high	% high
A+	1	0.2%	469	93.2%
A	2	0.4%		
A-	26	5.2%		
B+	1	0.2%		
B	76	15.1%		
B-	254	50.5%		
C+	94	18.7%		
C	15	3.0%		

1310-1400, and 19% indicated 1410-1500.[1] Similar thresholds and percentages were evident for orders that used SAT as a filter. Low SAT thresholds across orders were 18% for less than 1000, 27% for 1000-1100, 21% for 1110-1200, 17% for 1210-1300, 11% for indicated 1310-1400, and 6% for 1410-1500. High SAT thresholds across orders were 8% for 1000-1100, 12% for 1110-1200, 18% for 1210-1300, 7% for indicated 1310-1400, 19% for 1410-1500, and 35% indicated scores greater than 1500+.

PSAT and SAT score thresholds were consistently higher for orders by research universities in comparison to master's universities. The average low PSAT threshold score for research university orders was 1269 (about 90th percentile) versus 1034 for master's universities (about 50th percentile). Similar patterns were evident for SAT score thresholds. The average low SAT score threshold for research university orders was 1234 versus 1111 for orders by master's

[1] Old PSAT scores were converted to equivalent thresholds for new format: STILL NEED TO DO THIS

universities.

Zip code, state, and segment were the most commonly used geographical filters used across all orders. While we can account for the number of orders that filtered by zipcodes (N=278), we can only analyze patterns for the 208 orders from universities that provided the list of zipcodes filtered by.[2] These orders were made by two master's universities, primarily for in-state orders. Figure 9 shows the three-digit zip code filters used across these orders. The majority of orders (113 of 118) using zip code filters by the first master's university were to zip codes exclusively in the state where the university resides. The remaining 5 orders included in-state and neighboring state zip codes. Orders using zip code filters by the second master's university reveal similar patterns, except the majority of orders included a mix of in-state and neighboring state zip codes (70 of 108).

Figure 9: Filter by 3-digit zip code

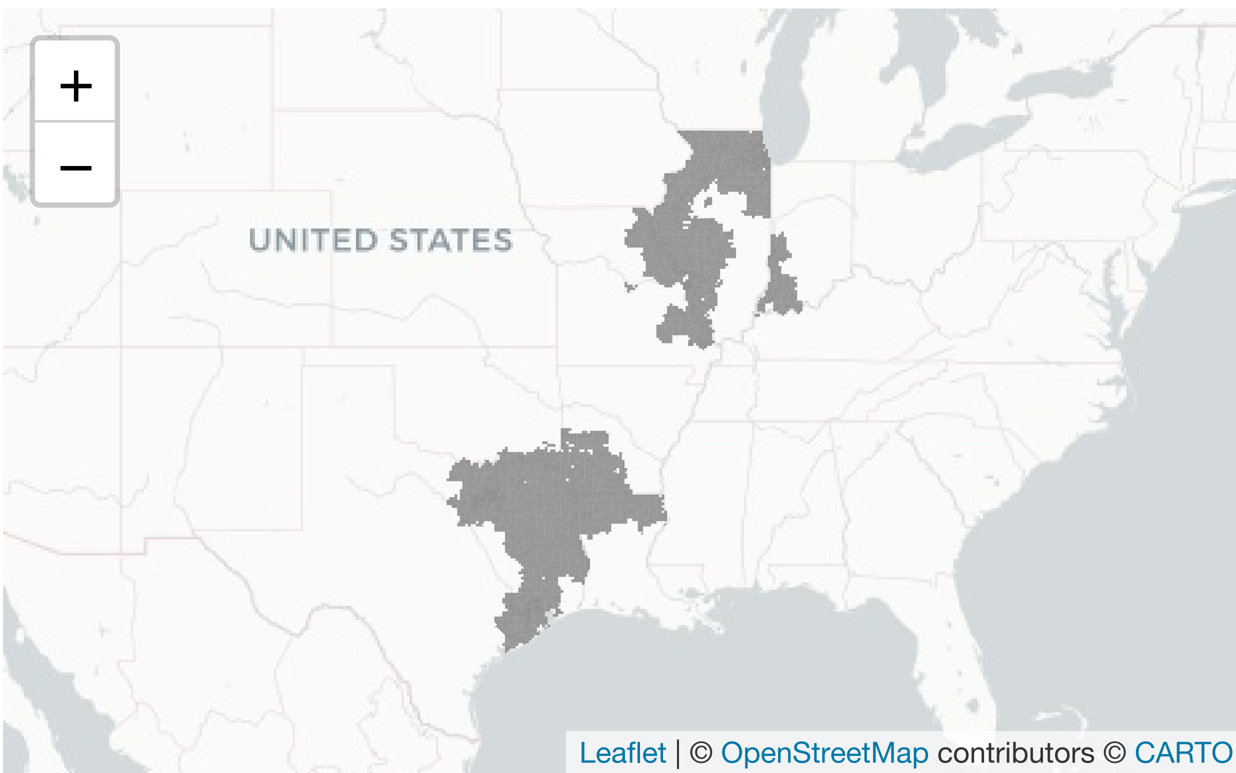


Table 5 [TABLE 5 DIFFICULT TO INTERPRET] shows states that were selected across the 175 orders using the filter. Generally, multiple-state filters were used across out-of-state prospect orders, whereas orders that filtered by only a single state were used for purchasing in-state prospects.

[2]The other 70 orders indicated a zip code filter; however, the actual zipcodes used to filter order lists were not provided to us after multiple requests

Table 5: Filter by state

University state	Purchased state(s)	Count
IL	IL	72
CA	Multi-state	28
IL	Multi-state	26
TX	Multi-state	19
CA	CA	18
TX	TX	9
MN	Multi-state	3

[THE TEXT A FEW PARAGRAPHS ABOVE EXPLAINING HOW SEGEMENT WORKS SHOULD BE MOVED HERE] The 22 orders using segment filters were made by two public research universities in the sample. Figures 6 and 7 show which neighborhood and high school segments were used across these orders and the characteristics of these segments. One university made 21 of the 22 orders using segment filters, and all 21 orders followed the same patterns of segments. These 21 orders filtered for 10 different neighborhood clusters (51, 53, 58, 60, 61, 63, 69, 70, 73, and 78). Orders also filtered by high school segment clusters 58, 63, 64, 65, 66, 68, 69, 70, 73, 75, and 79.

Figure 8 [MAYBE A FIGURE FOR THIS?] also shows that 76 (15%) and 24 (5%) of the 503 orders used a filter for race/ethnicity and gender, respectively. Most of the 76 orders using race/ethnicity filters specified multiple race/ethnicity groups. This includes 28 orders that filtered by Black, Native American, or Latinx prospects; 19 orders that filtered for Asian or White prospects; 7 orders that filtered for Native American or Latinx prospects; and 7 orders that filtered for Asian, White, or other race. The remaining orders filtered for only one race/ethnicity group, include 2 orders filtering for Native American prospects (American Indian, Alaska Native, and/or Native Hawaiian or Other Pacific Islander), 1 order filter for Black prospects, and 11 orders filtering for Latinx prospects. For the 24 orders using gender filters, 75% indicated female prospects and 25% indicate Male prospects.

3.1.3 Combination of Filters

[SHOULD SOME OF THIS BE MOVED TO RQ 3?] Universities in the study used 41 different combinations of filters to purchase prospects. The ten most commonly used combination of filters, which account for over 80% of all orders, are presented in Table 8. More than half of all orders analyzed used a combination of high school graduation class, zip code, GPA, and PSAT and/or SAT scores to filter prospect lists. This includes 143 orders (28%) that used PSAT scores, 107 orders that used SAT scores (21%), and 28 orders that used both

Table 6: 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 7: 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**

Table 8: Filter combos used in order purchases

Filters	**Count**	**Percent**
grad_class,zip,psat,gpa	143	28%
grad_class,zip,sat,gpa	107	21%
grad_class,state,race,sat,psat,gpa,rank	39	8%
grad_class,zip,sat,psat,gpa	28	6%
grad_class,state,sat,gpa	25	5%
grad_class,state,psat,gpa	20	4%
grad_class,state,race,psat,gpa	16	3%
grad_class,state,segment,gender,sat,psat,gpa	13	3%
grad_class,state,gpa,APscores	11	2%
grad_class,sat,geomarket	9	2%

PSAT and SAT (6%) in addition to graduation class, zip code, and GPA. Other orders used a similar pattern of filters except for using state geographic filters instead of zip code, including 20 orders using PSAT scores and another 25 orders using SAT scores.

About 8% of orders (39 of 503) used high school graduation class, state, sat, psat, gpa, and class rank filters while specifying for the race/ethnicity of prospects. The second most commonly used filter combination that specified the race/ethnicity of prospects includes 16 orders that used it in combination with graduation class, state, PSAT, and GPA filters.

The remaining combinations followed similar general patterns in targeting both the academic and geographical characteristics of prospects as the top combinations described above; however, they used other types of filters (e.g., gender, AP scores, segment, geomarket). Thirteen orders used graduation class, state, SAT, PSAT, and GPA filters in combination with segment and gender. Orders that used the segment filter used both neighborhood and high school clusters. For example, one specific order included a filter for census tracts assigned to neighborhood cluster 51, but further filtered by only including prospects from schools assigned to high school clusters 65, 68, 70, and 79 were included.

Eleven orders used graduation class, state, GPA in combination with APscores. AP score filters tended to be grouped into "fields" and varied across score thresholds. Most orders targeted prospects scoring from 3-5 on AP exams in either STEM fields (e.g., Physics, Calculus, Biology, Chemistry, Computer Science) or Humanities and Fine Arts (e.g., Spanish, French, Art History, Music Theory), although some STEM orders filtered for prospects scoring a 4 or 5 on their AP exans.

Lastly, nine orders used graduation class, SAT, and geomarket. These orders filtered for geomarkets within Texas and Louisiana. Louisiana geomarket orders targeted prospects in the Baton Rouge and Shreveport areas. Texas geomarkets filtered for include but are not limited to the Dallas/Ft. Worth areas, Central Gulf Coast, Wharton County, Victoria County, City of San Antonio, Southwest Houston Metropolitan Area, Brazos and Trinity Valley, Austin and Central Texas, Galveston area, East Texas.

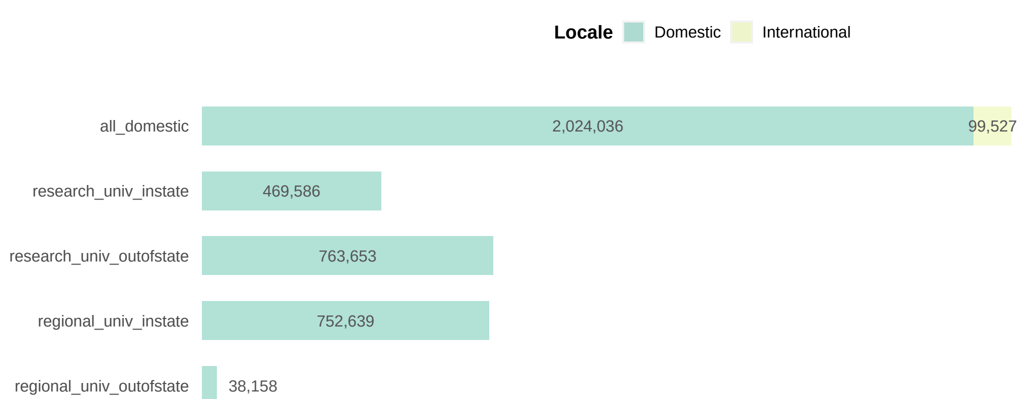
3.2 Characteristics of Prospects

Our analysis on the characteristics of prospects purchased by universities includes 405 orders resulting in 2,123,563 prospects. Figure 10 shows the total number of prospects by domestic versus international status. Of the over 2 Million prospects purchased, 95% of them were domestic students.

Figure 10 also shows the number of domestic prospects purchased by in-state versus out-of-state and by institutional type. Overall, the majority of prospects purchased across all orders by all institutions in the study were in-state students (60%). However, the percent of in-state versus out-of-state prospects varied across institutional type. Research universities purchased more students overall and a greater proportion of out-of-state students than master's universities. For example, research universities in the study purchased around 1.2 Million prospects of which 62% were out-of-state. In comparison, master's universities purchased 791,000 prospects of which only 5% were out-of-state students.

Below we also describe the racial, economic, and schooling characteristics of domestic prospect lists across institutional type and in-state versus out-of-state. The last sub-section then describes the characteristics of international prospects purchased.

Figure 10: Number of prospects purchased



3.2.1 Racial Characteristics

Figure 11 presents the racial characteristics of all domestic prospects resulting from the 405 purchased orders by in-state versus out-of-state for research and master's university purchases. Race/ethnicity of prospects is collected from the College Board's voluntary demographic questionnaire completed by students when taking the SAT; therefore, we report racial characteristics as self-identified and include the percentage of students that did not report their race/ethnicity. About 35% of all domestic prospects self-identified as White, 21% as Latinx, 15% as Asian, 5% as Black, 4% as Multiracial, and 20% did not report their race/ethnicity.

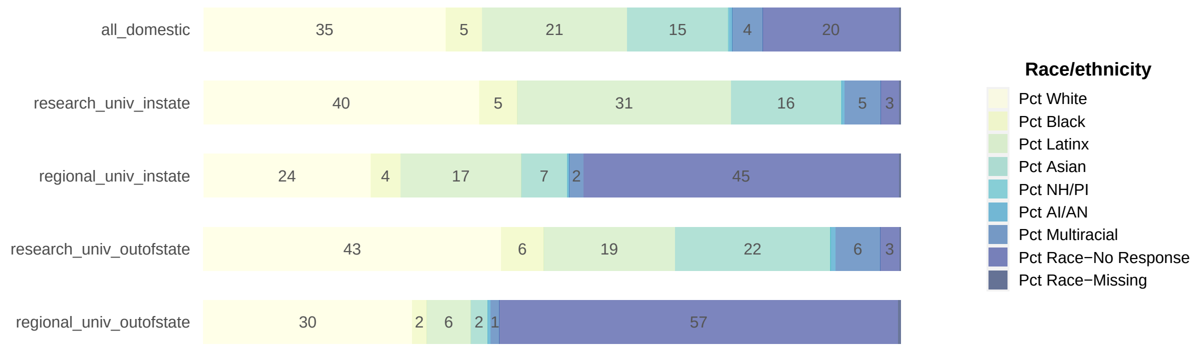
Out-of-state prospects purchased tended to be more White and Asian than in-state prospects purchased, although a larger percentage of in-state prospects did not report their race/ethnicity. For example, when universities in the study made order purchases for prospects residing in different states than where their campus is located, these lists resulted in prospect lists made up of 42% White students, 21% Asian students, 18% Latinx students, 6% Black, 6% multiracial, and 5% no response. In comparison, purchases for prospects residing in the same state as the institution's campus results in lists made up of 30% White students, 10% Asian, 22% Latinx, 5% Black, 3% multiracial, and 29% of students that did not report their race/ethnicity. While out-of-state prospect lists included a larger proportion of White and Asian students, these orders also include a critical mass of nearly 8,000 Native American students that can be glossed over when only looking at overall proportions.

The differences in the racial characteristics of in-state versus out-of-state prospects are likely also a function of purchases made by research versus master's universities. While research universities made more out-of-state than in-state prospect purchases, the differences in the racial characteristics of both groups were relatively small in comparison to purchases by master's universities. For example, White students made up 43% and 40% of out-of-state and in-state prospect lists purchased by research universities, respectively. In comparison, White students made up 30% of out-of-state prospect lists and only 24% of in-state prospect lists purchased by master's universities. However, purchases by master's universities also included a much larger proportion of students that did not report their race/ethnicity.

3.2.2 Economic Characteristics

Figure 12 presents the average median income of the zip code where prospects live by in-state versus out-of-state status for research and master's university purchases. Purchased prospects, across all orders by the 13 universities in the study, live in areas with an average median

Figure 11: Prospects purchased by race



household income of $92,000.

Overall, Figure 12 shows out-of-state prospects tended to live in more affluent areas than in-state prospects. Across all institution types, when universities in the study made order purchases for prospects residing in different states than where their campus is located, these lists resulted in prospects that live in areas where the average median household income is $100,000. In comparison, purchases for prospects residing in the same state as the institution's campus resulted in prospects that live in areas where the average median household income is $87,000.

This disparity is also likely driven by several differences across purchases by research versus master's universities. For example, out-of-state prospects purchased by research universities live in areas where the average median household income is $101,000, whereas in-state prospects purchased live in areas with a $91,000. However, the opposite pattern is evident for purchases by master's universities. Out-of-state prospects purchased by master's universities on average live in less affluent areas ($77,000 median household income) than in-state prospects ($84,000 median household income).

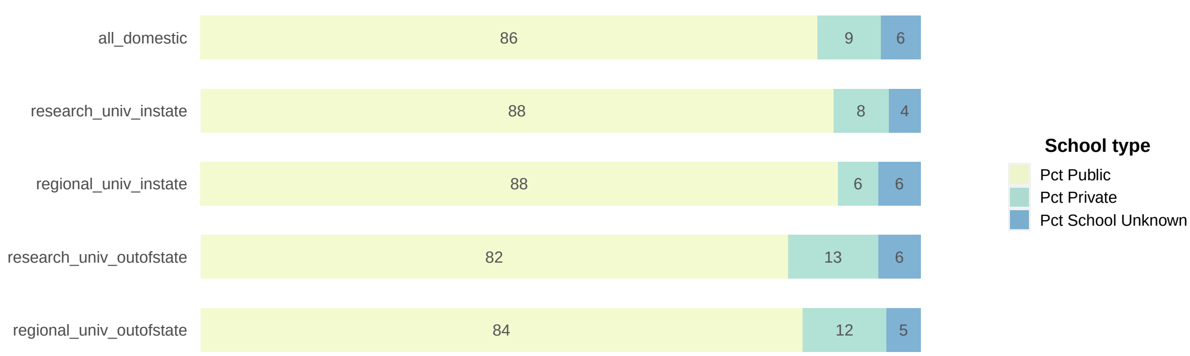
Figure 12: Prospects purchased by income

3.2.3 High Schools Attended

Given some of the College Board products link individual prospects to high schools for services like high school segment clusters, we are able to analyze some of the characteristics of high schools purchased prospects attend.

Figure 13 presents school type for purchased prospects by in-state versus out-of-state status for research and master's university purchases. Overall, 86% of prospects purchased attend public high schools, 9% attend private schools, and 6% did not report their high school. While these overall proportions are comparable to national averages, there are several differences across in-state versus out-of-state purchases by research and master's universities. For research universities, students attending private high schools made up a greater share of out-of-state prospect lists (13%) than in-state lists purchases (8%). Student list purchases by master's universities also exhibited this pattern, where private high school students made up 12% of out-of-state prospects versus 6% of in-state prospects purchased.

Figure 13: Prospects purchased by school type



3.2.4 International Prospects

Nearly 100,000 of the 2 Million prospects purchased were international students. Table 9 presents the countries from which these prospects were purchased, with XYZ representing the total number of prospects purchased by country. The top ten countries, which account for more than 60% of international prospects purchased across the 405 orders, include India (18%), China (10%), Singapore (6%), South Korea (6%), Canada (5%), United Arab Emirates (5%), Pakistan (4%), Taiwan (3%), Saudi Arabia (3%), and Thailand (3%).

3.3 Filter Criteria and Characteristics of Prospects

We analyze the relationship between filter criteria and the characteristics of purchased prospects in two different ways. First, we analyze prospect characteristics (e.g., race/ethnicity,

Table 9: Prospects purchased by international country

Country	# prospects	% prospects
India	17,626	17.9%
China	10,154	10.3%
South Korea	6,070	6.2%
Singapore	5,436	5.5%
Canada	5,321	5.4%
United Arab Emirates	4,842	4.9%
Pakistan	3,701	3.8%
Taiwan	2,949	3%
Saudi Arabia	2,948	3%
Thailand	2,542	2.6%

income, in-state versus out-of-state) across individual filters to understand broad patterns. Second, we analyze prospect characteristics across common combinations of filters. Here we use selected universities, purchases and/or localities that convey commonly observed or thematically important patterns across combinations of filters. We also contextualize the characteristics of purchased prospects by showing the characteristics of one or more comparison groups based on the selected examples.

3.3.1 Prospect Characteristics Across Individual Filters

Table 10 presents the characteristics of prospects by individual filters. For each column, averages are reported across all prospects that were purchased via orders using the specified column filter, which includes orders that used the specified filter in combination with other filters.[3]

Focusing on the racial characteristics of prospects, student lists with the largest percentages of White and Asian prospects result when orders use PSAT, gender, segment, or CBSA filters. For example, orders that specify a gender filter result in prospect lists that are less than 10% Black, Latinx, and/or Native American. This pattern is consistent in prospect lists that use segment or CBSA filters, although the disparity is not as large for orders using a PSAT filter (26% Black, Latinx, Native America). On the other hand, orders that filter by specifying particular race/ethnicity groups result in lists that have fewer White and Asian prospects and greater proportions of Black, Latinx, Native American, and multiracial prospects. This coincides with descriptive findings above that suggest more than half of all orders using a

[3]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 2,123,563 prospects

Table 10: Characteristics of prospects by filters

	All domestic	GPA	PSAT	SAT	HS rank	Race	Gender	Zip code	State	Segment	CBSA
Total N	2,024,036	1,078,989	733,556	824,497	824,497	286,996	39,546	165,924	827,652	186,519	146,313
Pct Race-No Response	20	18	14	21	21	3	3	4	20	17	3
Pct AI/AN	0	1	1	0	0	2	0	1	1	0	0
Pct Asian	15	14	16	13	13	9	38	13	13	26	28
Pct Black	5	6	5	6	6	11	1	8	6	2	2
Pct Latinx	21	20	20	19	19	38	6	27	19	7	8
Pct NH/PI	0	0	0	0	0	0	0	0	0	0	0
Pct White	35	36	40	36	36	28	47	43	36	43	53
Pct Multiracial	4	5	4	5	5	9	5	4	4	4	5
Median Household Income (mean)	91,839	91,925	94,803	91,530	91,530	84,743	110,587	87,861	91,377	113,165	117,222
Pct In-State	60	63	63	63	63	57	6	98	59	15	4
Pct Out-of-State	40	37	37	37	37	43	94	2	41	85	96
Pct Private	9	8	10	8	8	9	9	7	9	11	14
Pct Public	86	86	85	87	87	85	86	85	86	85	82
Pct School Unknown	6	6	6	5	5	6	4	9	5	3	4

race/ethnicity filter specified Black, Native American, and/or Latinx prospects.

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

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

Lastly, Table 10 shows the difference in proportions of prospects that attend public versus private schools does not change significantly across filters used. For example, orders that specify a CBSA result in student lists where on average 14% of prospects attend private schools, which is the maximum proportion across all filters. In comparison, orders that use zip code filter result in students lists with the minimum proportion of prospects attending private schools (7%).

3.3.2 Prospect Characteristics Across Combinations of Filters

3.3.3 Regional Zip Codes & Test Scores

We begin analyzing the characteristics of prospects across some of the most common combination of filters. Many of the orders in our analysis filtered by high school graduation class, PSAT scores, GPA, and zip code. Figure 9 and analyses above suggest orders using this combination of filters were made by master's universities to identify in-state and regional prospects. We "zoom" into orders by one of these master's universities, Texas A & M University- Texerkana, in order analyze in-depth patterns in the racial and economic characteristics of prospects that result from this combination of filters.

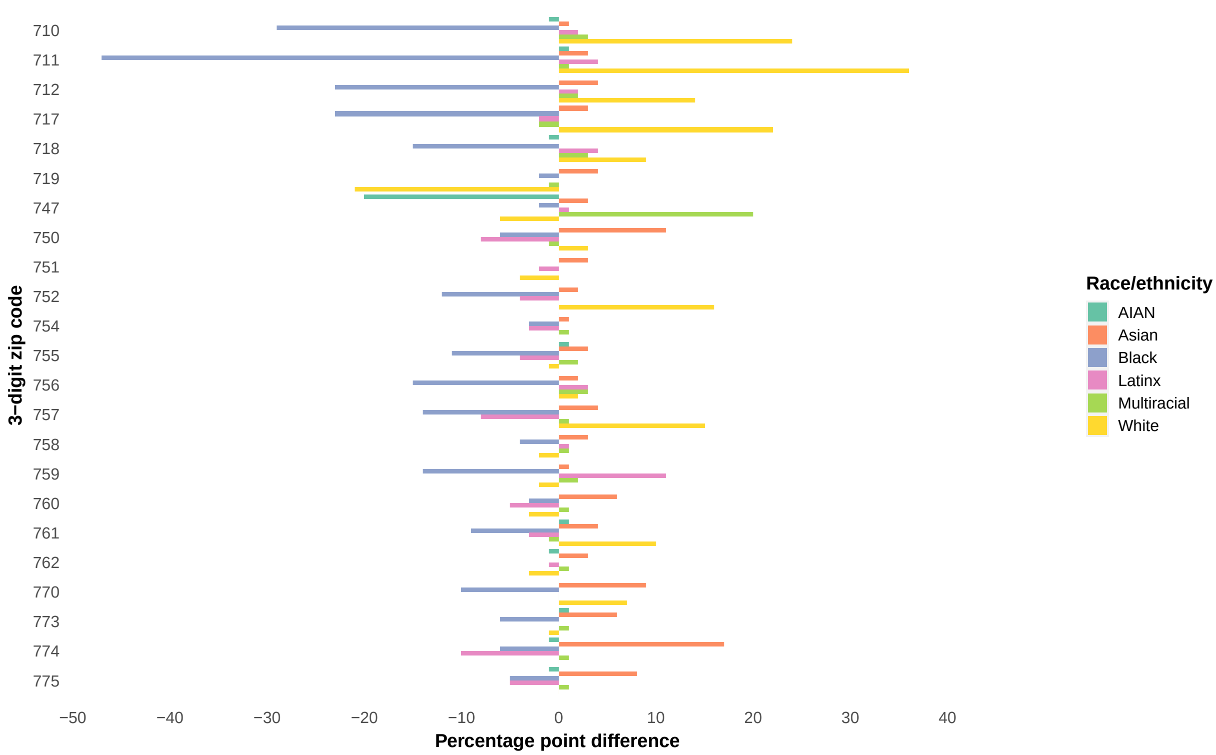
Texas A & M University- Texerkana made 65 orders using graduation class, PSAT scores, GPA, and zip code filters. These orders targeted 2019-2022 high school graduating classes with minimum PSAT scores ranging from 920-1300 and maximum SAT scores ranging from 970-1450. The university also filtered for prospects with GPAs ranging from a low of C+ to a high of A+. Lastly, prospects were also filtered using a series of 3-digit zip codes that included both in-state and neighboring state zip codes.

For each three-digit zip code used as an order filter, we compare the average racial and economic characteristics of the resulting purchased prospects to the zip code's population of 15-19 year-olds. We select the zip code population as the comparison group for purchase prospects filtered by graduation class, PSAT scores, GPA, and zip code filters for various reasons. First, the university included a three-digit zip code filter which encapsulates all students living within in a specified area (usually a City or County), which should hypothetically cast a wider, more equitable net than filtering explicitly by 5-digit zip codes. However, we analyze whether this wider net is compromised when it is used along with test scores and GPA. Secondly, master's universities are like to serve regional student markets, rather than the entire state where they are located. Therefore, we use a filtered zip code's population as a comparison group for prospects purchased within that zip code rather than all zip codes in the state from which prospects were not purchased from.

For example, the three-digit zip code 752 was included in 27 of the 65 orders that filtered across graduation class, PSAT scores, GPA and zip code. The 49 five-digit zip codes nested within the three-digit 752 zip code includes communities across the Dallas metropolitan area (see Figure X). The student lists for these orders resulted in 8,707 purchased prospects living in one of the 47 five-digit zip codes. About 40% of purchased prospects identified as White, 39% as Latinx, 8% Black, 5% Asian, and 3% multiracial. In comparison, the population of 15-19 year olds in these 49 five-digit zip codes are 24% White, 43% Hispanic, 20% Black, 3% Asian, and 3% multiracial.

Figure 14 presents the average percentage point difference between the racial/ethnic composition of students lists and of the 15-19 year old population across all zip codes filtered by the master's university in this analysis. For example, Zip Code 752 in Figure 14 shows a 16 percentage point difference between White prospects purchased living in the zip code and the overall percentage of White 15-19 year olds living in the zip code (40%- 24% = 16 percentage points), suggesting White prospects are overrepresented in purchased lists relative to the population of their home zip code. Similarly, the figure shows a -12 percentage point difference between the Black prospects purchased from the zip code and the percentage of Black 15-19 year olds living in the zip code (8% - 20% = -23 percentage points), suggesting Black prospects are underrepresented in purchased lists relative to the population of their home zip code.

Figure 14: Texas A&M purchases by zip code and race



Overall, Figure 14 suggests prospect lists from orders that filtered using graduation class, PSAT scores, GPA, and zip code tend to be more White and Asian and less Black and Latinx relative to the population of 15-19 year olds from zip codes filtered by. The overepresentation of White prospects in comparison to zip code populations ranged from 2 to 36 percentage points for 11 of the 23 zip codes filtered by, whereas three zip codes had proportional representation (0 percetage point difference). The remaining 9 zip codes had an underrepresentation of White prospects, where eight orders ranged from 1 to 6 percentage points and one order had -21 percentage points. The overrepresentation of Asian prospects purchased across the 23 zip codes ranged from 1 to 17 percentage points.

Black prospects were underrepresented relative to zip code populations across all zip codes used and in the greatest magnitude across all racial/ethnic groups. The underrepresentation of Black prospects purchased across the 23 zip codes ranged from 2 to 47 percentage points. Latinx students were also underrepresented across 12 of the 23 zip codes, although the magnitude was not as large as (ranging from 1 to 10 percentage points). Three of the zip codes filtered by had proportional representation of Latinx students (0 percentage point difference), whereas the remaining zip codes had an overrepresentation ranging from 1 to 4 percentage points.

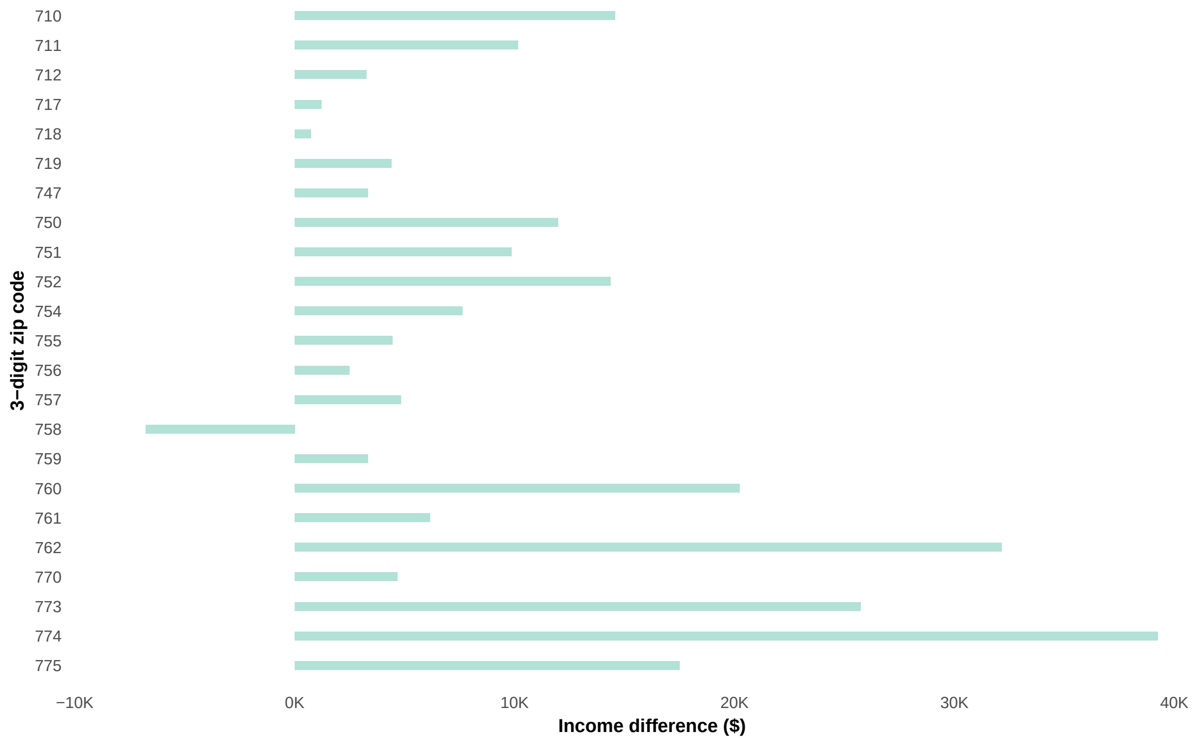
Economic disparities are also evident when we compare the average median income of prospects relative to the average median household of the zip code population. Figure 15 presents the difference in average median household income between prospects (measured at the 5-digit zip code level) and the average median household income across all nested 5-digit zip codes within the 3-digit filters used. Because both prospects' and population income is measured at the zip code level across 5- versus 3-digits, a disparity indicates more prospects living in affluent 5-digit zip codes were purchased than the average median household income across all 5-digit codes within the 3-digit filter.

Figure 15 shows student lists resulting from 22 of the 23 zip code filters included more affluent prospects than the average population of those zip codes. This disparity was largest for prospects purchased from 774 zip codes (communities within Richmond, Texas), which had an average median income nearly $40,000 greater than the average median income of the population across all nested 774 zip codes. Prospects purchased from 758 zip codes (communities within Palestine, Texas) were the only across all filters to have an average median income less than the population across all nested zip codes ($43,000 versus $50,000).

3.3.4 Out-of-State Zip Codes & Test Scores

Other common combinations of filters were used by research universities in the study to target out-of-state prospects. Some of these orders filtered by graduation class, state, CBSA,

Figure 15: Texas A&M purchases by zip code and income



segment, SAT or PSAT, and GPA. We "zoom" into orders by The University of Illinois at Urbana-Champaign in order to analyze in-depth patterns in the racial and economic characteristics of prospects that result from this combination of filters.

The University of Illinois at Urbana-Champaign made eight orders using graduation class, state, CBSA, segment, SAT or PSAT, and GPA. These orders targeted 2019-2023 high school graduating classes with minimum PSAT/SAT scores ranging from 1220-1240 and maximum PSAT/SAT scores of 1450. The university also filtered for prospects with GPAs ranging from a low of B- to a high of A+. Prospects were also geographically filtered across State/CBSAs and segments. For States/CBSA, the university filtered across some of the largest, most populated metropolitan areas of the country (including but not limited to Atlanta, New York, Philadelphia, Boston, Washington D.C., Detroit, Phoenix, Miami, Orlando, Baltimore, Denver, Raleigh). As described above, segment filters across orders used both neighborhood and high school clusters. These eight orders filtered for neighborhood clusters 51 (with sll high school clusters), 53 (with high school cluster 70), 58 (all high schools), 60 (with high school clusters 65,70,79), 61 (with high school cluster 65), 63 (with high school clusters 68, 70), 69 (with high school clusters 65, 79), 70 (with high school clusters 65, 68, 70, 75), 73 (with all high schools), 78 (with high school cluster 66). Orders also included all high school categorized under high school cluster 79.

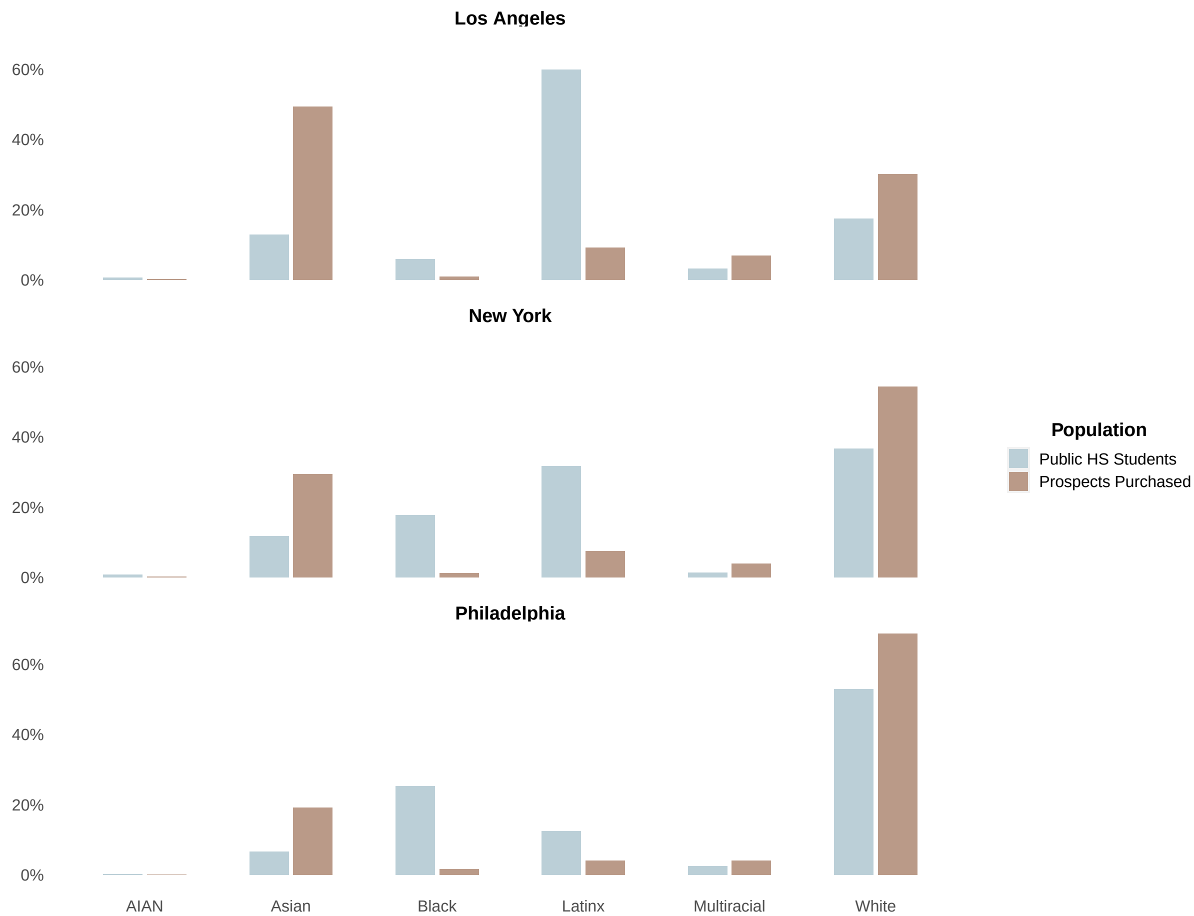
We analyze orders by the University of Illinois at Urbana-Champaign that use these filters across several metropolitan areas by comparing the average racial and economic characteristics of the resulting purchased prospects to the metropolitan areas' overall population' of public high school students. We select the population of public high school students within the metropolitan area as a comparison group for several reasons. First, similar to our analysis of zip code filters above, the university included entire metropolitan areas as filters that should hypothetically provide an equitable opportunity for all prospects living in the area to be included in student lists purchased by the university. However, the combination of segment and additional academic filters may result in disparities across which prospects are included in comparison to the average population of the metropolitan area.

Figure 16 shows the racial/ethnic characteristics of purchased prospects versus the population of students attending public high schools in three metropolitan areas that were included across all eight orders by the University of Illinois at Urbana-Champaign using graduating lass, state, CBSA, segment, SAT or PSAT, and GPA filters. For example, the top panel shows the resulting student lists for University of Illinois at Urbana-Champaign that targeted prospects within the Los Angeles metropolitan area using these filters. The brown bars indicate the students lists for these orders resulted in 18,420 purchased prospects living in the metropolitan area. About 30% of purchased prospects identified as White, 49% as Asian, 1% as Black, 9% as Latinx, and 7% as multiracial. In comparison, the blue bars in the figure indicate the population of public high school students in the Los Angeles metropolitan area are 18% White, 13% Asian, 6% Black, 60% Latinx, and 3% Multiracial.

Across orders using graduation class, segment, SAT or PSAT, and GPA filters within the Los Angeles, Philadelphia, and New York Metropolitan areas, prospect lists resulted in higher percentages of White and Asian students relative to the population of public high school students within each metropolitan area. The overrepresentation of White prospects in student lists relative to the population of public high school students ranged from 12 to 17 percentage points across the three metropolitan areas. Purchased prospects within the Los Angeles metropolitan areas exemplified the largest disparity for Asian students, with 49% of purchased prospects identifying as Asian relative to the 13% of public high school students identifying as Asian within the metropolitan area (a 36 percentage point difference).

Figure 16 shows Black and Latinx prospects were underrepresented relative to public school students across all three metropolitan areas. Orders made within the Philadelphia metropolitan area exemplify the largest magnitude in this disparity for Black students, with Black students making up less than 2% of purchased prospects while making up more than 25% of all public high school students in the metropolitan area. The underrepresentation of

Figure 16: Metro area purchases by race



Black prospects in comparison to public high school students was 16 percentage points for the New York and 3 percentage points for the Los Angeles metropolitan areas. On the other hand, the Los Angeles metropolitan area exemplified the largest disparity for Latinx students (9% Latinx purchased prospects versus 60% Latinx public high school students). The underrepresentation of Latinx prospects in comparison to public high school students was 8 percentage points for the Philadelphia and 24 percentage points for the New York metropolitan areas.

Figure 17: Metro area purchases by income

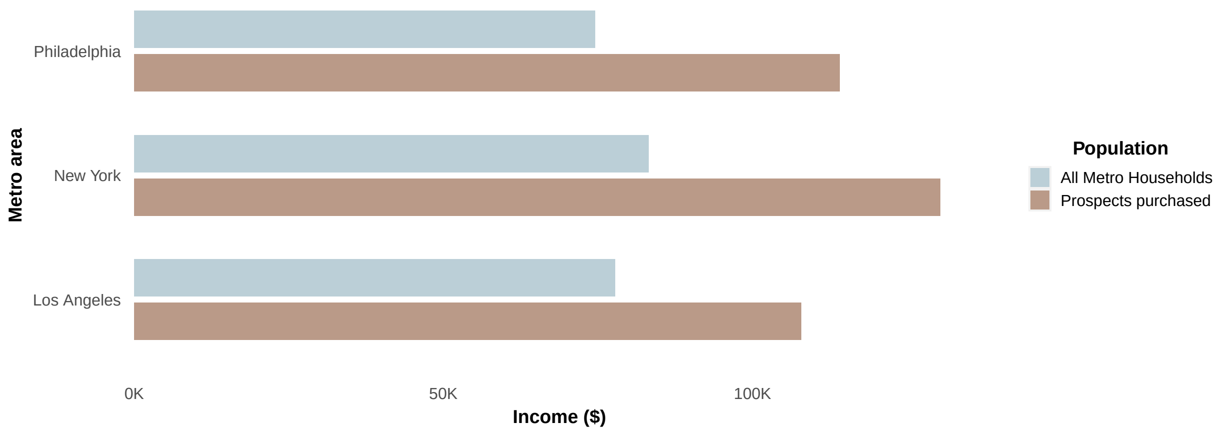


Figure 17 presents the average median household income of purchased prospects (taken at the 5-digit zip code level) in comparison to the median household income of the entire metropolitan area. For example, the median income across all households in the Philadelphia metropolitan area is $75,000, whereas prospects living within the metropolitan area purchased by the University of Illinois at Urbana-Champaign had an average median household income of $114,000. Prospects purchased tended to have higher median average household incomes than the average across all households within the Los Angeles and New York metropolitan areas also. The difference was nearly $50,000 for New York and $30,000 for Los Angeles.

3.3.5 Women in STEM

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

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

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

Our analysis first focuses on comparing the racial characteristics of Texas prospects whose profiles were purchased to the population of 15-19 year olds in their home zip codes. The university purchased at least one prospective students' profile from 203 of the 1,935 zip codes in Texas. Figure X presents the racial characteristics of prospects to the population of 15-19 year olds in these 203 zip codes. The figure shows two general trends consistent across orders targeting Women in STEM. First, White and Asian prospects are overrepresented relative to the population of 15-19 year olds in their home zip codes. For example, nearly 40% of all purchased prospects are White while 38% of the 15-19 year olds in their home zip codes are also White. This difference is much larger for Asian prospects, who make up nearly 30% of all purchased prospect profiles but only make up about 6% of the population of 15-19 year olds in their home zip codes. Second, Black and Latinx prospects are underrepresented

[4]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).

to their zip code populations. Black and Latinx prospects make up 2% and 20% of all purchased prospects, respectively, while their home zip code's population of 15-19 year olds are on average 10% Black and 36% Latinx. It's important to note that only 3 of the 559 prospects purchased across Texas were Native American. While looking at proportions across the population of 15-19 year olds in zip codes invisibilizes the number of Native American students in relation to other racial/ethnic groups, the 3 prospects are relative to a total of 3,623 Native American 15-19 year olds living in these 203 zip codes.

Figure 18: FIGURE COULD BE SOME VARIATION OF THESE DATA

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

Figure X also shows the economic characteristics of prospects and prospective students in

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

Lastly, we use AP participation data from the Texas Education Agency to compare the racial characteristics of prospects whose profiles were purchased by the university to the population of AP science test takers in Texas.[5] The racial and economic inequities in access to AP coursework and disparities in passing rates are well-documented (CITE). However, we compare prospects to test takers to illustrate how using AP score range filters, rather than just proxying STEM interest by students with have the ability to and take AP science coursework, further exacerbates inequities in whose profiles are purchased.

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

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

Figure 19: FIGURE COULD BE SOME VARIATION OF THESE DATA

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