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Closing the Gap: The Effect of Reducing Complexity and Uncertainty in College Pricing on the Choices of Low-Income Students[†]

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High-achieving, low-income students attend selective colleges at far lower rates than upper-income students with similar achievement. Behavioral biases, intensified by complexity and uncertainty in the admissions and aid process, may explain this gap. In a large-scale experiment we test an early commitment of free tuition at a flagship university. The intervention did not increase aid: rather, students were guaranteed before application the same grant aid that they would qualify for in expectation if admitted. The offer substantially increased application (68 percent versus 26 percent) and enrollment rates (27 percent versus 12 percent). The results suggest that uncertainty, present bias, and loss aversion loom large in students' college decisions. (*JEL* I22, I23, I24, D31, I28)

Gaps in educational attainment between low- and high-income students are large and have grown in recent decades. Among children born in the 1980s, those from the bottom quartile of family incomes are 50 percentage points less likely to attend

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college than those from the top quartile. And while 54 percent of children born into the top income quartile earn a bachelor's degree, only 9 percent of those in the lowest quartile do so (Bailey and Dynarski 2011).

These differences stem in part from disparities in academic preparation. But even among well-prepared students, there are substantial gaps in college enrollment and the quality of college attended (Hoxby and Avery 2012). The under-representation of low-income students at selective colleges likely exacerbates both educational and income inequality.[1] While there is no experimental evidence on the effect of college quality, several studies suggest that attending a college of higher quality (e.g., a flagship instead of a less-selective four-year school or a community college) increases both educational attainment and earnings (Hoekstra 2009; Zimmerman 2014; Dillon and Smith 2018).

Among high-achieving students, it is application behavior that drives income differences in college quality. Hoxby and Avery (2012) find that the majority of low-income, high-achieving students apply to zero selective schools, even though doing so would likely lower their costs (Cohodes and Goodman 2014), increase their chances of completing a college degree, and increase their future wages (Hoekstra 2009; Zimmerman 2014; Andrews, Imberman, and Lovenheim 2016).

Standard models of human capital investment fall short in explaining these behaviors. Though a lack of information about the (net) cost of college or suitability for an elite school could in theory lead low-income students to underinvest in education, previous interventions targeting these information frictions have shown only modest success (Bettinger et al. 2012; Hoxby and Turner 2013; Bergman, Denning, and Manoli 2019; Gurantz et al. 2019; Hyman 2020, although see Jensen 2010 for an exception). Insights from behavioral economics suggest that students' choices deviate from the classical model in predictable ways. Many observed behavioral patterns, such as present bias, overreliance on routine or defaults, and debt aversion, are particularly pronounced for those facing economic scarcity (as are low-income students) and complex decisions (as presented by the higher education and financial aid systems) (Mullainathan and Shafir 2013). Within such an environment, small changes in choice architecture can lead to large changes in behavior.

We use a randomized controlled trial to test whether targeted, personalized communications, which reframe but do not increase financial aid, can alter the college decisions of low-income students. The intervention, the HAIL (High Achieving Involved Leader) Scholarship,[2] was designed in the spirit of previous interventions that make small changes to the framework of decision-making.

We collaborated with the University of Michigan in Ann Arbor, the state's most selective college, in this study.[3] In the Fall of 2015 and 2016, we sent personalized mailings to high-achieving, low-income seniors in Michigan's public high schools.

[1] We interchangeably use the terms "high quality," "selective," and "elite" throughout to refer to selective institutions. Such schools tend to spend more per student, as well as enroll high-achieving students who are inputs into the education production function (Black and Smith 2006).

[2] The acronym HAIL is a reference to the University of Michigan's fight song. "HAIL Michigan" is plastered on t-shirts, bumper stickers, water bottles, tube tops, underwear, beer coolers, dog coats, and billboards across the state and beyond. Go Blue!

[3] Barron's ranks schools from "least competitive" to "most competitive" based on a combination of average GPA, SAT scores, and acceptance rates. The University of Michigan is in the "highly competitive" or second highest category.

The mailings encouraged students to apply to the university and pledged four years of free tuition and fees to those admitted.[4] Parents of these students also were mailed a letter about this offer, and their school principals were notified by email.

In each of two cohorts of rising seniors, we identified roughly 2,000 high-achieving, low-income students at the state's public schools. These students attended 500 different high schools. We randomized treatment at the school level, since we expected there would be spillovers that would have biased a within-school design. One-half of the 500 schools were assigned to treatment and one-half to control.

We identified students for the intervention using administrative data from the Michigan Department of Education (MDE) (Michigan Department of Education 2020a, b). We targeted those who qualified for subsidized school meals, the only proxy for income available in these data. All students in Michigan's public high schools are required to take the SAT (until 2016, the ACT), which is used by the state to satisfy federal testing requirements. The SAT is administered for free, during the school day, at students' own schools. We focused on students whose scores and grades (contained in the state data) made them reasonable targets for recruitment according to our research partners in the University of Michigan admissions office (the criteria are detailed in Section II).

We find very large effects of the intervention offer on application and enrollment rates at the University of Michigan and, more generally, on college choice. The likelihood of applying to the University of Michigan more than doubled, from 26 percent among controls to 68 percent among students offered treatment. The share enrolling at a highly selective college also more than doubled, from 12 percent to 27 percent, with this effect operating completely through enrollment at the University of Michigan.

We find that one-quarter of the enrollment effect (4 percentage points) is driven by students who would not have attended any college in the absence of the treatment. The balance would have attended a community college or a less selective four-year college. The offer of the scholarship diverted no students from colleges as or more selective than the University of Michigan: that is, there was no "poaching" from other selective schools. Nor did the offer *increase* attendance at other selective schools, a plausible effect of mailings that told students that they were strong candidates for admission to the University of Michigan.

The magnitudes of these effects are much larger than those in previous interventions with similar goals (Bettinger et al. 2012; Hoxby and Turner 2013; Goldrick-Rab et al. 2016; Bergman, Denning, and Manoli 2017; Gurantz et al. 2019; Oreopoulos and Ford 2019; Hyman 2020). Several dimensions of the HAIL intervention set it apart, and plausibly explain the size of its effect.

The HAIL Scholarship provides an *early*, *unconditional guarantee* of free tuition. The *early* nature of the offer locks in a price guarantee at the time of the application decision. The four-year *guarantee* reduces the uncertainty of future college costs, by converting the likely prospect of aid into a guarantee. Previous research suggests that information is most effective when delivered at the time of decision-making

[4] The HAIL scholarship offer was not a guarantee of admission to the University of Michigan and admissions officers were not informed about which students received the HAIL scholarship offer. HAIL students who applied to the University of Michigan went through the standard admissions process.

(Fernandes, Lynch, and Netemeyer 2014; Fischer and Wagner 2018; Patterson, Pope, and Feudo 2019).

The offer is *unconditional*: while students must still apply and be admitted, they do not have to fill out any paperwork or go through any verification to qualify for the scholarship.[5] Although the costs of learning about and applying for financial aid are small compared to its value (and the benefits of college), previous research suggests that even minor and short-term costs can have an outsize influence on the decisions of myopic students (Hoxby and Turner 2013, Bulman 2015, Pallais 2015, Goodman 2016, Oreopoulos and Ford 2019).

The HAIL offer effectively changes the *default* option for students, in that no action is required to accept it. Previous research indicates that people use shortcuts in complex decision environments, and that changing defaults can therefore dramatically influence behavior (Johnson and Goldstein 2009, Beshears et al. 2013, Pallais 2015, Marx and Turner 2019).

The intervention, in the end, did not substantively alter the cost of attending the University of Michigan. Students in the treatment and control groups who enrolled at the university wound up with virtually identical aid packages.[6] The University of Michigan meets the financial need (as defined by national aid formulas) of all of its students. Those with incomes as low as those in our sample almost invariably qualify for free tuition and fees, as well as for living expenses. Because of these preexisting policies, the HAIL guarantee was rarely binding on the University. The behavioral changes induced by the guarantee indicate that certainty, while virtually costless to the school, was extremely valuable to potential students.

Our results show that a low-cost intervention that removes behavioral and administrative obstacles can profoundly alter student choices. We add to a growing body of research that shows that seemingly minor differences in policy design can have profound effects on real economic outcomes. In ongoing work, we track the effects of the intervention on college major, persistence, and graduation. In the long term, we will examine the effect of the induced changes in educational attainment on earnings and other measures of adult well-being.

I. Background

A. *Income Gaps in College Quality and Why They Matter*

A long literature informs the design of the HAIL scholarship and our understanding of income-based gaps in college going.

Just 12 percent of college students come from the bottom fifth of the family-income distribution, while 28 percent are from the top fifth. This imbalance is even larger at

[5] While submitting aid forms was not required to receive the HAIL Scholarship, applicants were encouraged to do so. University of Michigan staff prodded students to complete forms, and 99 percent of HAIL Scholars who enrolled at the University of Michigan did so, which substantially increased their aid.

[6] Note that this comparison, while informative, does not have a causal interpretation, since the treatment increased the likelihood of attending the university.

the most selective colleges (Chetty et al. 2017)[7], which have more students from the top 1 percent of the income distribution than from the entire bottom half.

Undermatching accounts for some of this gap in college selectivity. Students are said to undermatch when they are much more academically qualified than typical peers at their chosen school. Only 38 percent of Chicago Public Schools students who qualify for very selective colleges attend one (Roderick, Coca, and Nagaoka 2011). Similarly, Bowen, Chingos, and McPherson (2009) found that, among students in North Carolina in 1999, 40 percent did not attend the highest-tier institution for which they were likely eligible given their academic performance. This concurs with a study of two nationally representative cohorts of high school graduates from 1992 and 2004 (Smith, Pender, and Howell 2013).

Hoxby and Avery (2012) and Dillon and Smith (2017) find that the main driver of mismatch is student application choices rather than schools' admissions decisions. That is, low-income students wind up at schools of lower selectivity not because they were rejected by the better schools but because they never applied to them. Dillon and Smith (2017) find that, among the students who undermatch, 72 percent applied to no closely matched college; just 6 percent applied to such colleges but were rejected. Hoxby and Avery (2012) show that many qualified students apply to no selective colleges at all.

In Michigan, as in the rest of the country, there are large differences in college choices between low- and higher-income students. Among students whose high academic achievement makes them plausible candidates for a selective school, low-income students (defined as those eligible for federally subsidized school meals) are 4 percentage points less likely to attend *any* college than their higher-income peers (see Figure 1). Gaps in college selectivity are even wider than gaps in college attendance: low-income students are 8 percentage points less likely than more advantaged peers to attend a highly selective school.

More selective schools typically offer more aid to low-income students, making them cheaper than less selective schools (see Table 1). The net cost of attendance at the University of Michigan for in-state students with family income below $30,000 is $3,249.[8] This makes the University of Michigan the cheapest four-year option for low-income students in the state; their net cost of attendance is $7,058 at Michigan State University, and $12,316 at Eastern Michigan University. For students with slightly higher family income (between $30,000 and $48,000), the net cost of attendance at the University of Michigan is $5,575.[9] For these students, only a community college is a cheaper option than the University of Michigan (nearby Washtenaw Community college costs $4,455).[10]

Higher college quality is associated with higher graduation rates and salaries. Research indicates that at least part of this relationship is causal (Hoekstra 2009, Zimmerman 2014, Dillon and Smith 2018). The University of Michigan has

[7] The authors refer to these institutions as the "Ivy Plus" and include the eight Ivy League schools plus MIT, Stanford, Duke, and the University of Chicago.

[8] From College Scorecard data.

[9] This is roughly 130–185 percent of the federal poverty threshold for a family of four, and corresponds to the upper income thresholds for free or subsidized meals in school.

[10] Table 1 includes four illustrative schools, but the point holds more broadly. For students in the two lowest income categories, the University of Michigan in Ann Arbor is the most affordable bachelor's-degree-granting school in the state.

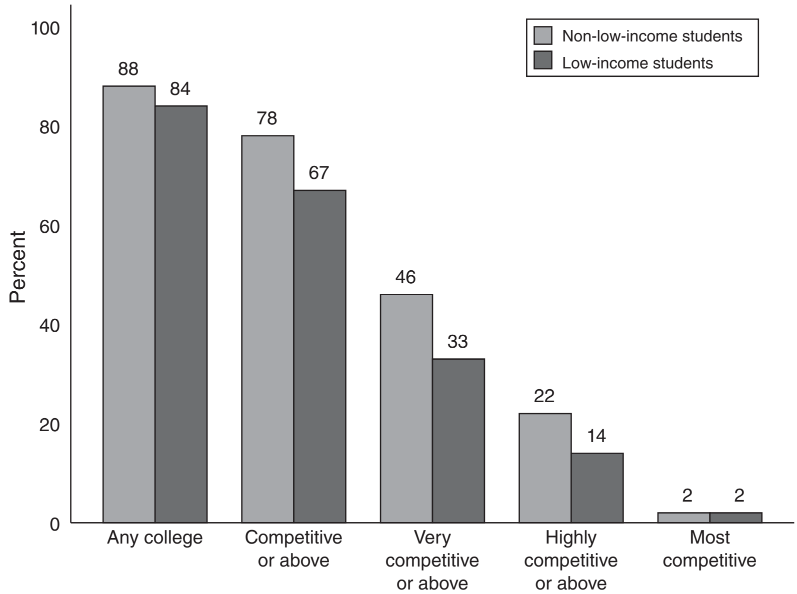

Figure 1. Selectivity of Colleges Attended by High-Achieving Michigan Students, by Income

Notes: Sample is eleventh-grade students in Michigan public schools in 2013 who meet HAIL GPA and ACT criteria. College enrollment measured at first institution attended in fall 2014. Low-income means eligible for free or reduced-price lunch in eleventh grade. Selectivity categories from Barron's selectivity index.

Source: Michigan administrative data

Table 1—Characteristics of Selected Universities in Michigan

	University of Michigan	Michigan State University	Eastern Michigan University	Washtenaw Community College
Barron's selectivity category	Highly competitive	Very competitive	Competitive	Not rated
Average annual net cost for in-state students				
All students	\$14,860	\$18,576	\$14,406	\$5,286
Students with family income \$0–30K	\$3,249	\$7,058	\$12,316	\$3,912
Students with family income \$30K–48K	\$5,575	\$13,116	\$12,951	\$4,455
Graduation rate	0.91	0.79	0.41	0.15
Median salary after attending	\$63,400	\$53,600	\$39,300	\$29,200

Notes: University of Michigan refers to the Ann Arbor campus. Average annual net cost is "derived from the full cost of attendance (including tuition and fees, books and supplies, and living expenses) minus federal, state, and institutional grant/scholarship aid, for full-time, first-time undergraduate Title IV-receiving students." Average net cost is reported for this group as well as for subsets of students in the two lowest income brackets reported by College Scorecard (\$0–\$30,000 and \$30,001–\$48,000). For reference, the cutoff for free lunch eligibility for a family of four is \$33,104 (130 percent of the federal poverty line), and for reduced-price eligibility it is \$47,638 (185 percent of the federal poverty line) as of 2019. The graduation rate for the four-year schools is the proportion of first-time, full-time students who complete a bachelor's degree within six years; for Washtenaw Community College it is the proportion of first-time, full-time students who complete a two-year degree within three years. Median salary represents "the median earnings of former students who received federal financial aid, at 10 years after entering the school." All quotes are from College Scorecard.

Source: College Scorecard, https://collegescorecard.ed.gov (accessed May 30, 2019) a 91 percent graduation rate (within six years) and an average alumni salary of over \$63,000 (within ten years of attendance). The comparable statistics at nearby Eastern Michigan University are 41 percent and \$39,300. Shifting low-income students to the University of Michigan is therefore likely to increase both their educational attainment and adult income.

B. *Lessons from Previous Literature and Interventions*

The facts laid out above present a puzzle: given their substantial benefits and relatively low costs, why aren't selective colleges the destination for more low-income, high-achieving students? It is difficult to square this behavior with the human capital model, in which people weigh the expected costs and benefits of schooling, choosing the option that maximizes the return over a lifetime.

We might conclude (and evidence shows) that students are uninformed, and that providing information about the costs and benefits of college would make a difference in their decisions (Avery and Kane 2004, Dynarski and Scott-Clayton 2006, Oreopoulos and Dunn 2013).[11] But multiple studies have found that information alone does not change student behavior (Bettinger et al. 2012; Hoxby and Turner 2013; Bergman, Denning, and Manoli 2019; Gurantz et al. 2019; Hyman 2020; although see Jensen 2010 for an exception). In the most closely related study, Bettinger et al. (2012) found that providing professional assistance with federal financial aid forms increased the likelihood of completing two years of college by 8 percentage points (off a base of 40 percent), but providing detailed information about financial aid had no effect.

Behavioral economics provides plausible explanations for why low-income, high-achieving students attend selective colleges at far lower rates than their higher-income peers.[12] Research in the lab and in the field has identified a number of behavioral phenomena that can explain consistently observed patterns in educational decision-making. First, people often exhibit time-inconsistent preferences and appear present-biased (Frederick, Loewenstein, and O'Donoghue 2002; Stanovich, West, and Toplak 2012). They act in ways inconsistent with their stated goals for the future, and overemphasize short-term costs and benefits (Ainslie 1975, Laibson 1997). Due to their still-developing brain systems, which affect cognitive functioning and critical thinking, adolescents are particularly susceptible to present bias (Bettinger and Slonim 2007; Chapman, Gamino, and Mudar 2012; Galván 2012). For example, students are swayed by small, short-term college costs, such as application fees and the effort required to take the SAT or ACT; in a rational educational investment model, these costs would be dwarfed by long-term benefits and would not affect choices on the scale observed in many interventions that reduce these barriers (Hoxby and Turner 2013, Bulman 2015, Pallais 2015, Goodman 2016, Oreopoulos and Ford 2019).

[11] Classical economic models acknowledge that information is costly to acquire. In our context, the returns to a college degree are so large, and the opportunity costs of high school students so low, that it is virtually impossible to generate a scenario in which the costs of acquiring information outweigh the benefits.

[12] In this section, we draw on several excellent review papers about the behavioral economics of education: Jabbar (2011); Koch, Nafziger, and Nielsen (2015); Lavecchia, Liu, and Oreopoulos (2016); French and Oreopoulos (2017); and Damgaard and Nielsen (2018).

Loss aversion, where a loss is felt more strongly than an equal-sized gain, may cause students to underinvest in education, which requires certain loss of time, effort, and money, with the prospect of future gains (Kahneman and Tversky 1979). Similarly, debt aversion, which has no place in a traditional investment model, may prevent many students from borrowing to finance college (Field 2009; Scott-Clayton 2012; Caetano, Palacios, and Patrinos 2019). Students from lower income backgrounds seem particularly prone to debt aversion (Baum and Schwartz 2015, Calender and Jackson 2005). Research has documented the important roles loss and debt aversion play in education and career decisions (e.g., Field 2009).

Finally, psychologists and sociologists point to the importance of social identity in decision-making. People tend to behave in ways consistent with their social identity and the norms of their social groups (Benjamin, Choi, and Strickland 2010). Making certain aspects of students' identities more salient (e.g., their academic achievement) may prompt them to make choices more in line with that part of their identity (e.g., applying to a selective college). Framing financial aid as a scholarship, rather than a need-based grant, calls attention to the high-achieving dimension of a student's identity, rather than their socioeconomic status (Avery and Hoxby 2003).

All of the phenomena discussed above may be particularly important in contexts where there are many choices and the decision-making process is complex. In the presence of information overload or choice overload, when there are too many factors or too many options to fully consider, people tend to resort to heuristics or mental shortcuts to simplify the decision (Kahneman 2003). This could mean sticking to the status quo (which may be inaction) or picking the most prominent option, even if it is not the best one. College application and financial aid feature many choices and intense complexity. In this context, the default may mean choosing the nearest community college or regional university. Indeed, two-thirds of all college students attend an institution within 25 miles of home, and nearly 85 percent attend an institution within 100 miles (authors' calculations using the National Postsecondary Student Aid Study, 2016 cohort).

In the presence of information overload, seemingly small changes to the environments in which people make choices can have large consequences. Interventions aimed at simplifying or assisting with the application and financial aid process, for instance, produce significant increases in student enrollment and persistence in college (e.g., Bettinger et al. 2012, Castleman and Page 2016). Additionally, changing the default option presented to people, without changing anything about the options available, has been shown to strongly influence the choice they make (Johnson and Goldstein 2009, Beshears et al. 2013, Pallais 2015, Marx and Turner 2019).

II. Data, Sample, and Randomization

Our target population is high-achieving, low-income students in Michigan. We identify these students using longitudinal, student-level administrative data that contain the universe of students attending public high schools in the state.[13]

[13] Data come from the Michigan Department of Education (MDE) and the Michigan Center for Educational Performance and Information (CEPI) (Michigan Department of Education 2020a, b).

We identify high-achieving students using high school GPA: which comes from student transcript data; and SAT score: which comes from mandatory, in-school eleventh grade testing.[14] Admissions officials at the University of Michigan set the GPA and score cutoffs; they are analogous to the criteria the school uses when gleaning prospective recruits from national data on ACT and SAT takers. Grades and scores do not determine admission; like most highly selective colleges, the University of Michigan uses multiple criteria, including extracurricular activities, to decide who gets in. For this intervention, qualifying SAT scores start at 1100 while qualifying GPAs start at 3.3. Students with higher test scores faced a lower GPA threshold (and vice versa). Students in the sample had an average GPA of 3.8 and SAT of 1260.

We do not have information on family income. We identify low-income students using data on qualification for the federal subsidized-lunch program. Students with family income below 130 percent of the federal poverty line qualify for a free lunch, while those with incomes up to 185 percent of the poverty line can get a subsidized lunch. In 2018, these thresholds were $32,630 ($46,435) for a family of four. Two-thirds of our sample qualifies for a free lunch and the remainder for a reduced-price lunch.[15]

Schools in the sample are widely dispersed throughout the state. While there are concentrations of schools in the major metropolitan areas, there are also many schools in the Upper Peninsula and in other rural areas (see Figure 2). Of the 100,000 juniors in Michigan's public high schools, about 2,000 students in 500 schools meet the income and academic criteria for our intervention each year: 2,108 students from 529 schools for the first cohort and 1,802 students from 497 schools for the second.[16] The typical school in Michigan has only a handful of high-achieving, low-income students. The modal school in our experimental sample has one student meeting the HAIL eligibility criteria (see online Appendix Figure 1).

A. *Randomization*

We assign treatment status at the level of the high school. All students in a school who meet the income and academic criteria are assigned the same treatment status. We do this because we hypothesize treatment spillovers within schools, which (in the case of within-school randomization) would attenuate estimated effects toward zero. We stratify the sample (into four groups) by the number of HAIL-eligible students in each school and randomize within each stratum.[17]

For the first cohort, the randomization resulted in 1,057 treated students and 1,051 control students in 262 treated schools and 267 control schools. In the second

[14] In the 2015–2016 school year, which corresponds to the second cohort of our intervention, the state switched from using the ACT to the SAT as the eleventh grade standardized exam. We convert all ACT scores to SAT scores using official concordance tables.

[15] In Michigan, students automatically qualify for subsidized meals if their family receives means-tested benefits such as food stamps or cash welfare. Qualification occurs through a data match between the education and human services administrative systems.

[16] Pooling the two cohorts, 28,267 juniors met the academic criteria but not the income requirement, while 52,377 students met the income requirement but did not meet the achievement criteria.

[17] For the second cohort, schools that had newly entered the sample (because they had no qualifying students in the first cohort but did in the second) were randomly assigned using the same method. Similarly, some schools exited the sample during the second cohort. See online Appendix Table 1 for details on how many schools were in the sample for each cohort.

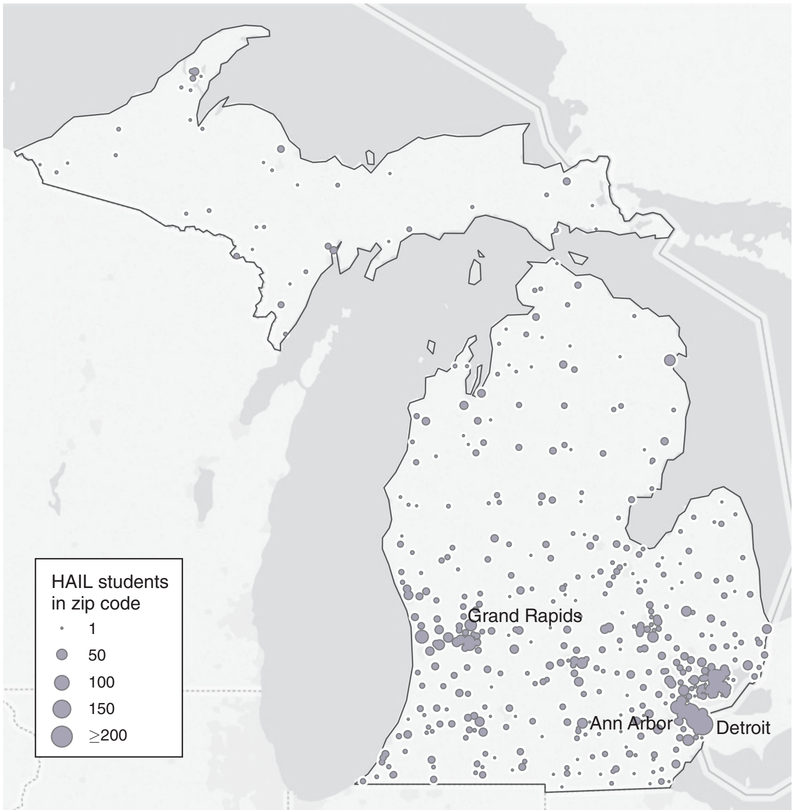

Figure 2. HAIL Students Are Widely Dispersed across Michigan, First and Second HAIL Cohorts

cohort, 875 students in 238 high schools were in the treatment group, while 927 students in 259 high schools were in the control group.

Sample characteristics are shown in Table 2. The table shows tests for balance (within each stratum) between treatment and control groups. Forty percent of the schools in the treatment and control groups are in the southeast region of the state, near Ann Arbor, Lansing, and Detroit. Another 14 percent of schools are in the largely rural Upper Peninsula. The remaining schools are scattered across the Lower Peninsula, with many concentrated in the Grand Rapids area. Over half of the schools are rural, one-third are suburban, and the remainder urban.

The overwhelming majority (78 percent) of sample students are White (non-Hispanic), reflecting the strong correlation (in Michigan and the United States) between academic achievement and race. Nine percent are Black (non-Hispanic) and 6 percent are Hispanic.[18] A majority are female (59 percent). All of these statistics track patterns of academic achievement in the state and nationwide.

A glance through the table shows balance on all characteristics. This is substantiated by a joint F-test, which reveals that, together, these characteristics do not predict

[18] Students are coded as Hispanic if they identify as Hispanic, regardless of race. For students of multiple races, a single race category is assigned according to the following hierarchy: Black, Native American, Asian, Hawaiian/Pacific Islander, White.

Table 2—Balance Table: Mean Characteristics for Schools by Treatment Status, First and Second HAIL Cohorts

Characteristic	Control mean	Treated mean	p-value
Upper Peninsula	0.150	0.130	0.518
	(0.021)	(0.020)	
West Central	0.449	0.476	0.545
	(0.030)	(0.030)	
Southeast	0.401	0.394	0.864
	(0.029)	(0.030)	
Suburb	0.340	0.360	0.592
	(0.028)	(0.029)	
City	0.129	0.100	0.273
	(0.020)	(0.018)	
Town or rural	0.530	0.540	0.838
	(0.030)	(0.030)	
Distance from University of Michigan (UM) in miles	93.2	96.4	0.597
	(4.691)	(4.824)	
Number of eleventh grade students in school	189.1	175.1	0.162
	(8.493)	(8.343)	
Number of HAIL students in school	3.8	3.9	0.613
	(0.177)	(0.210)	
Share female	0.571	0.605	0.102
	(0.016)	(0.015)	
Share White (non-Hispanic)	0.772	0.787	0.566
	(0.017)	(0.016)	
Share Asian	0.061	0.057	0.718
	(0.008)	(0.009)	
Share Black (non-Hispanic)	0.094	0.087	0.685
	(0.013)	(0.011)	
Share Hispanic	0.053	0.057	0.681
	(0.008)	(0.009)	
Share American Indian, Alaska Native, or Native Hawaiian	0.019	0.012	0.253
	(0.006)	(0.004)	
Share free lunch eligible	0.709	0.692	0.450
	(0.015)	(0.015)	
Share reduced-price lunch eligible	0.291	0.308	0.450
	(0.015)	(0.015)	
Average SAT (or equivalent)	1254	1259	0.200
	(2.805)	(3.017)	
Average GPA	3.82	3.83	0.263
	(0.006)	(0.006)	
Share limited English proficient	0.002	0.004	0.395
	(0.001)	(0.001)	
Share receiving special ed services	0.009	0.013	0.387
	(0.003)	(0.004)	
Share who sent ACT/SAT scores to UM	0.365	0.377	0.580
	(0.015)	(0.015)	
F-test p-value		0.118	
Average predicted probability of highly selective college attendance	0.126	0.132	0.421
	(0.005)	(0.005)	
Number of school-years	526	500	1,026
Number of students	1,978	1,932	3,910

Notes: All analyses conducted at the school-year level; p-values are from a t-test of the coefficient on treatment status from a regression of the characteristic on treatment and strata dummies. F-test is from a joint significance test predicting treatment based on the characteristics listed here (excluding the summary index) as well as strata dummies. Summary index calculated from parameters of an OLS regression estimating the relationship between observable characteristics and a binary indicator for attending a college as competitive as the University of Michigan. Standard errors clustered at the school level in parentheses. All regressions use robust standard errors clustered at the school level.

Source: Michigan administrative data and University of Michigan Office of Enrollment Management data treatment status. Additionally, a summary index created based on pre-intervention characteristics (discussed in more detail in Section VC) reveals that students from the treatment and control group had similar propensities to attend a highly selective college. We test the sensitivity of results to controlling for covariates.

III. Intervention

We designed the treatment to address the behavioral barriers discussed earlier. We drew on insights from previous interventions attempting to reduce income-based gaps in college choices, as well as the behavioral economics literature on decision-making.

Students in the treatment group received personalized packets at their homes in the first week of September of their senior year of high school. Students in the control group received materials typically sent to potential applicants by the University of Michigan, including booklets describing the school and its financial aid.

The treatment materials, designed by admissions staff, were large, glossy, and brightly colored in the university's signature "maize and blue" coloring. We recommended that they be eye-catching, and clearly from the University of Michigan, to reduce the likelihood that students would discard the packets without opening them (see pictures in online Appendix Section A.1). In previous interventions, mailings sent in plain envelopes from an unfamiliar source were largely ignored or disregarded as fraudulent (Hoxby and Turner 2013, Goldrick-Rab et al. 2016).

Inside the packet, a letter from the president of the University of Michigan praised the recipients' academic achievement and encouraged them to apply for admission. The letter then guaranteed four years of tuition and fees if the student were accepted. The value of this offer was also expressed in dollar terms ($60,000). The offer was framed as a scholarship, rather than a need-based grant. In fact, the student's low-income status was referenced nowhere in the mailing.

The mailing stated prominently that applicants did *not* have to complete financial aid forms (the Free Application for Federal Student Aid (FAFSA) and the College Scholarship Service Profile) in order to receive this scholarship; the only condition was admission to the University of Michigan. Eliminating the *requirement* to fill out the forms at the time of applications was intended to address a key behavioral bias: administrative burdens incurred in the present weigh heavily relative to uncertain benefits in the future (Hoxby and Turner 2013; Bulman 2015; Pallais 2015; Goodman 2016; Oreopoulos and Ford 2019). Because aid staff were concerned that the unconditional guarantee would dissuade students from completing aid forms, the mailings also encouraged completion of the FAFSA and Profile.[19]

A large, bright insert reiterated the scholarship offer in a format that resembled a coupon. Additional "coupons" guaranteed that fees would be waived for all applications for admission and aid. These physical coupons were intended to make the offers feel as concrete as possible.

The packet also contained materials that the University of Michigan sent to all of its potential applicants: a flyer describing application and admissions and

[19] Nearly all (99 percent) HAIL scholars who enrolled at the University of Michigan ultimately filled out the FAFSA and Profile. We find no significant differences in the likelihood of completing financial aid forms between treatment and control students who ultimately enrolled at the University of Michigan.

brochures describing the school. These materials encouraged students to apply to the University of Michigan by November 1, which is the "early action" deadline for the school.[20] The University of Michigan admits most of its incoming class through early action; students therefore have the best chance of being admitted if they apply by that date. Students would still be eligible for the scholarship if they applied by the standard deadline of February 1.

Information was also mailed to parents, and emailed to principals, of eligible students (see online Appendix Sections A.2 and A.3). Letters to parents, mailed two weeks after the student packets, described the scholarship and encouraged them to help their children apply. Communications with principals, sent in late August, explained the program, listed eligible students, and asked the principal to transmit the information to school staff who supported students in their college applications.[21]

IV. Empirical Strategy

We evaluate the effect of the HAIL scholarship on application, admission, enrollment, and persistence at the University of Michigan using internal data from the university (University of Michigan Office of Financial Aid 2020; University of Michigan Office of Enrollment Management 2020a, b). To measure enrollment and persistence at institutions nationwide, and to measure college selectivity, we rely on Michigan Department of Education (2020b) data, which contain information on college enrollment for all students in the treatment and control groups through the National Student Clearinghouse (NSC). We compare the outcomes of treatment and control students, estimating the following models by ordinary least squares (OLS):

$$(1) \qquad Y_{jt} = \beta_0 + \beta_1 D_j + \beta_2 S_{jt} + u_{jt},$$

$$(2) \qquad Y_{jt} = \gamma_0 + \gamma_1 D_j + \gamma_2 S_{jt} + \gamma_3 Z_{jt} + u_{jt},$$

where Y_{jt} is an outcome of interest at school j for cohort t. We collapse the individual student data to the school-cohort level and conduct analysis on these means.[22] The variable D_j is an indicator equal to 1 if the school is randomized to the treatment group and 0 if the school is randomized to the control group (note that schools keep their randomization status from the first cohort to the second cohort, see online Appendix Table 1). The term S_{jt} is a vector of strata dummies.[23] In some models, we

[20] Many selective colleges have an early application window for students who are particularly interested in that school. Some schools accept early applications only from the students who agree to enroll if admitted ("early decision"). Others, like the University of Michigan, inform students of their admission by the beginning of January but do not require students to accept the early offer ("early action").

[21] We did not assign the multiple treatment arms that would have allowed us to tease out the effects of the student, principal, and parent communications of the treatment. We thought we lacked sufficient statistical power for such an exercise, since we planned the experiment with an expectation of effects much smaller than those we obtained.

[22] Unless otherwise noted, we conduct all analyses at the school-year level; results are consistent when conducted at the student level, see online Appendix Table 4.

[23] The strata include indicators for the number of HAIL students in the school in the first year the school was randomized into the intervention (1, 2, 3, or 4 or more, with interactions indicating if the school was new to the sample in the second year of the intervention).

also include a vector of controls, Z_{jt}, which are listed in Table 2. In all analyses, we cluster standard errors by school, since treatment was assigned at this level.

Note, β_1 and γ_1 are the parameters of interest and measure the causal effect of being randomized into the treatment group, i.e., the estimated effect of the Intent to Treat (ITT). These parameters represent the treatment effect on the outcomes of interest, with schools weighted equally.[24]

Since we observe the outcomes for all students, and therefore all schools, there is no attrition due to non-response. We do not observe whether a student actually receives the information packet (i.e., is effectively treated), and students assigned to the control group cannot be treated, so we do not adjust for noncompliance.

As described in our pre-analysis plan, we conduct subgroup analyses to check for heterogeneity in the treatment effect.[25] These subgroup analyses help to identify the potential mechanisms through which HAIL affected application and enrollment. We summarize our heterogeneity with a single index (based on individual and school-level characteristics) predicting the likelihood that a student would have attended a selective college in the absence of the intervention.

We also examine heterogeneity for several specific subgroups of interest. Previous research suggests that low-income, high-achieving students who have few similar peers are less likely to attend selective institutions than those who are surrounded by similar peers (Hoxby and Avery 2012). Of particular interest is whether the HAIL scholarship was effective in raising application and enrollment rates among these isolated students (as found in a previous intervention designed to increase application rates of low-income students to selective institutions, Hoxby and Turner 2013). We proxy for isolation by region (Southeast, West Central, or Upper Peninsula), urbanicity (city, suburban, or town/rural), and the number of HAIL eligible students in the school.[26] Additionally, we evaluate heterogeneity by gender (male versus female), race (White, Black, Hispanic, Asian), and two measures of economic disadvantage.

V. Results

A. *Evidence of HAIL Awareness from Website Activity*

Were we to find no effect of the intervention, we would want to understand whether the materials went unread, or if the message they contained was ineffective in changing behavior. We therefore create a crude measure of whether students and parents opened and read the personalized mailings. We assigned each student a personalized web address and included it in the student packets, along with encouragement to log on to get more information about the HAIL Scholarship and University

[24] Estimates are similar when weighted by the number of sample students in each school.

[25] We show tests for balance in these subgroups in online Appendix Table 2. This study is registered at the randomized trial registry of the American Economics Association under RCT ID AEARCTR-0001831, with DOI 10.1257/rct.1831.

[26] Research has suggested that a high school's prior ties with a school predicts whether a student will attend (Hoxby and Avery 2012). We test this hypothesis by evaluating heterogeneous treatment effects as a function of schools' baseline enrollment rate at University of Michigan at Ann Arbor.

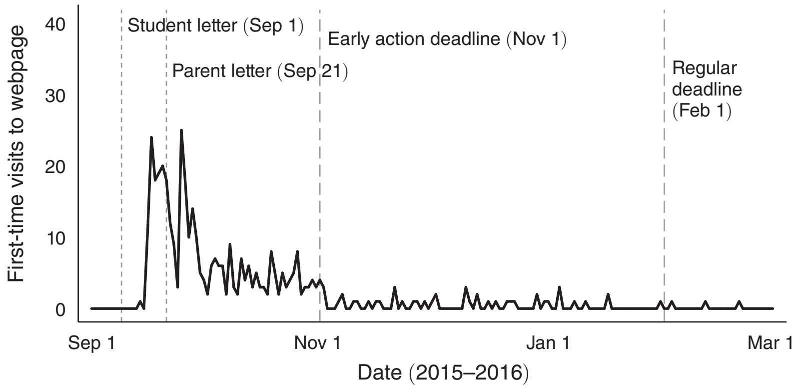

Figure 3. First-Time Visits to HAIL Webpages, First HAIL Cohort

Note: Unit of analysis is a first-time visit to the personalized URL associated with a treated HAIL student, aggregated by date.

Source: University of Michigan Office of Enrollment Management data

of Michigan. To drive students to the site, we offered them a free University of Michigan t-shirt.

About 40 percent of students offered HAIL visited the website at least once. This provides a lower bound on the number of students who read the packet, as many may have read the packet but not visited the website. Among students who visited the website, the average number of views was 5.5, with a median of 3.

First-time visits to the website are concentrated in the days after student and parent letters were mailed (Figure 3). Spikes occur a few days after the student letter was mailed and after the parent letter was mailed. This suggests that some parents prodded their children to log onto the website, since only the student packet contained login instructions.[27]

B. *Application, Admission, and Enrollment at the University of Michigan*

Students in treated schools were substantially more likely to apply to, gain admission to, and enroll at the University of Michigan at Ann Arbor than those in control schools (see online Appendix Table 3 for regression estimates and Figure 4 for treatment and control means).

At control schools, 26 percent of low-income, high-achieving students applied to the University of Michigan, compared to 68 percent at treatment schools. That is, the treatment increased the application rate by 42 percentage points. Results were virtually identical across the two cohorts.[28]

[27] The pattern is similar for the second cohort, though (due to delays in printing packets) student and parent letters were sent only three days apart (see panel C of online Appendix Figure 2). In addition to first-time page views, we also track total page views of personalized HAIL websites. See panels B and D of online Appendix Figure 2 for graphs of the total number of visits to HAIL websites for the first and second HAIL cohorts, respectively.

[28] We pool the two cohorts for most analyses; results separately by cohort are available upon request.

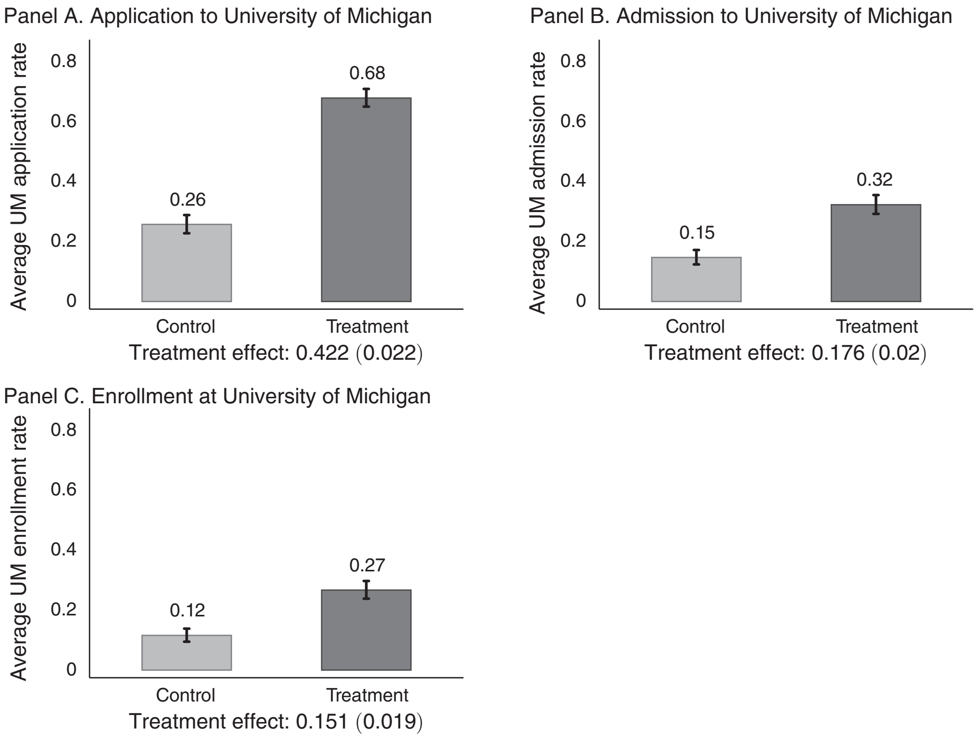

Figure 4. Estimated Effect of HAIL Scholarship on University of Michigan Application, Admission, and Enrollment, First and Second HAIL Cohorts

Notes: All analyses done at the school-year level. Ninety-five percent confidence intervals shown based on standard errors clustered at the school level. Application, admission, and enrollment measured in the summer and fall following expected high school graduation. Admission and enrollment are unconditional on application. Treatment effects estimated from a regression of the outcome on an indicator for treatment status and strata dummies. Robust standard errors clustered at the school level reported in parentheses.

Sources: Michigan administrative data and University of Michigan Office of Enrollment Management data

The intervention materials encouraged students to apply by the early action deadline of November 1.[29] Early application is a signal of a student's commitment to a school, so the attractiveness of the scholarship offer could have changed the timing of application for inframarginal as well as marginal students. Early application is already a popular choice for University of Michigan applicants; of students in the control group who applied, around three-quarters applied early action. We find that the intervention did not change this proportion, with three-quarters of the effect on application coming from students induced to apply early and the remaining quarter from students who were moved to apply regular decision. (See online Appendix Table 5 for full results on application timing.) Though we cannot observe application behavior at schools other than the University of Michigan, this suggests that the

[29] Students who apply by the early action deadline are typically notified of their admission status by the end of the calendar year. While early *decision* deadlines are binding, i.e., students must enroll if accepted, the University of Michigan uses an early *action* deadline, which does not compel students to enroll if admitted.

HAIL offer did not change the level of commitment to the school among those who applied.

These large differences in application rates translated into large differences in admissions rates. The (unconditional) admission rate was 15 percent in control schools and 32 percent in treated schools, a treatment effect of 17.6 percentage points. This is the net effect of the treatment on the joint likelihood of applying to and being admitted to the University of Michigan.

We do not have experimental evidence of the effect of the intervention on admission conditional upon application because application is affected by the treatment. Another way to put this is that treatment is not randomly assigned among *applicants*. However, comparing conditional admission rates gives a sense of the qualifications of the marginal applicant. Of the 589 control students who applied, 52.5 percent were accepted; of the 1,306 treated students who applied, 45.6 percent were accepted (see online Appendix Table 6). Note that the overall acceptance rate to the University of Michigan was 28.6 percent in 2016–2017, indicating that the applicants in our sample (including those induced to apply) are more qualified than the average applicant.[30]

Students in the treatment group were significantly more likely to enroll at the University of Michigan than those in the control group.[31] The (unconditional) enrollment rate for students in the control schools is 12 percent while in the treatment schools it is 27 percent. This translates into an increased enrollment of about 150 low-income students for each of the two cohorts.

Treatment effects estimated by differences in means (shown in Figure 4), a regression controlling for strata (Model (1), shown in the first column of online Appendix Table 3), and a regression controlling for strata and additional school covariates (Model (2), shown in the second column of online Appendix Table 3) are virtually identical.[32]

C. *Heterogeneity in Effects by Baseline Propensity to Enroll in a Selective Institution*

In this section we examine how our causal estimates differ by students' (predicted) baseline propensity to attend a school as selective as the University of Michigan.

We generate an index variable that captures how likely a student would be, in the absence of the intervention, to attend a selective school. We predict this index from the parameters of an OLS regression that estimates the relationship between observable characteristics and a binary indicator for attending a college as competitive

[30] Source: University of Michigan Office of Enrollment Management data (University of Michigan Office of Financial Aid 2020; University of Michigan Office of Enrollment Management 2020a, b). In the subsequent year, which corresponds to the second cohort of the HAIL intervention, the overall acceptance rate was 26.5 percent.

[31] In addition to our standard sampling-based inference, we test the likelihood of obtaining our estimated treatment effect on University of Michigan enrollment (as well as other key enrollment margins) using randomization-based inference. In this approach, randomness comes from assignment of a fixed number of units to treatment rather than sampling from a super-population. The conclusions are unchanged (and the *p*-values are nearly identical): the intervention treatment effects we find are highly unlikely to have occurred by chance. See online Appendix Section B for details.

[32] For the remainder of the paper, we report treatment effects estimated controlling for strata only. Regression results including all controls are in online Appendix Tables 8, 10 through 12, and 14 through 17.

as University of Michigan. We estimate this regression equation using data on two cohorts of low-income, high-achieving students who were seniors before the HAIL experiment. The regression includes student characteristics (ACT score, GPA, race, gender, an indicator for persistent economic disadvantage) as well as school characteristics (urbanicity, region, number of HAIL students in the school).[33] We use these estimated coefficients to predict the likelihood of going to a selective college for our experimental sample.

Figure 5 plots means of application, admission, and enrollment against this index. We display scatterplots with 20 equally sized bins of students, where the x-value is the within-bin mean of the index. A quadratic line is fitted through the binned points. For each outcome, we show scatterplots by treatment status; vertical bars indicate 95 percent confidence intervals on each point estimate.

Focusing first on the application decision (panel A), we see a strong, positive relationship in the control group between the index and the observed likelihood of applying to the University of Michigan. That is, in our sample, students whose observable characteristics predict they will attend a highly selective institution are those most likely to apply to the University of Michigan. This positive relationship is attenuated in the treatment group. The HAIL intervention increased applications *most* among students who were observably *least* likely to attend a highly selective school. The effects are also large in the middle of the distribution, but near zero at the top.

Hoxby and Avery (2012) show that it is the application decision that primarily drives income gaps in attending a selective school. But while application is a necessary step toward enrolling in a selective school, it is not sufficient: a student also has to be admitted. Note that we examine the unconditional likelihood of admission, since the decision to apply is itself an experimental outcome. On the admission margin, we see near zero effects at both the top *and* the bottom of the distribution. The HAIL intervention had little effect on the admission of those students whose characteristics predict they are least likely, and most likely, to attend a highly selective institution. The admissions effects are concentrated in the middle of the distribution, where HAIL boosted both application and admission rates.

The pattern for enrollment is quite similar to that for admission: it is the mid-range of the predicted index that yields most of the enrollment effects. At the bottom, many students induced to apply were not admitted, while at the top there was little effect on any outcomes. HAIL most affected the ultimate outcomes of those whose observable characteristics placed them in the middle of this predicted index.

A key challenge for HAIL (and any policy intended to increase diversity in colleges) is targeting outreach with limited information. By setting the academic bar for recruitment too high, we won't reach plausible admits; by setting it too low, we create a lot of disappointed applicants. The admissions office consistently expressed an aversion to "giving students false hopes."[34] Our administrative data on academic achievement are sparse and arrive with a lag. We have no information

[33] The estimated coefficients from this exercise are shown in online Appendix Table 13.

[34] Some colleges deliberately try to increase their application in order to reduce their admission rate, and thereby, boost their rank in reviews of colleges published by outlets such as *US News and World Report*. Their decisions throughout this project suggest that the University of Michigan does not follow this strategy.

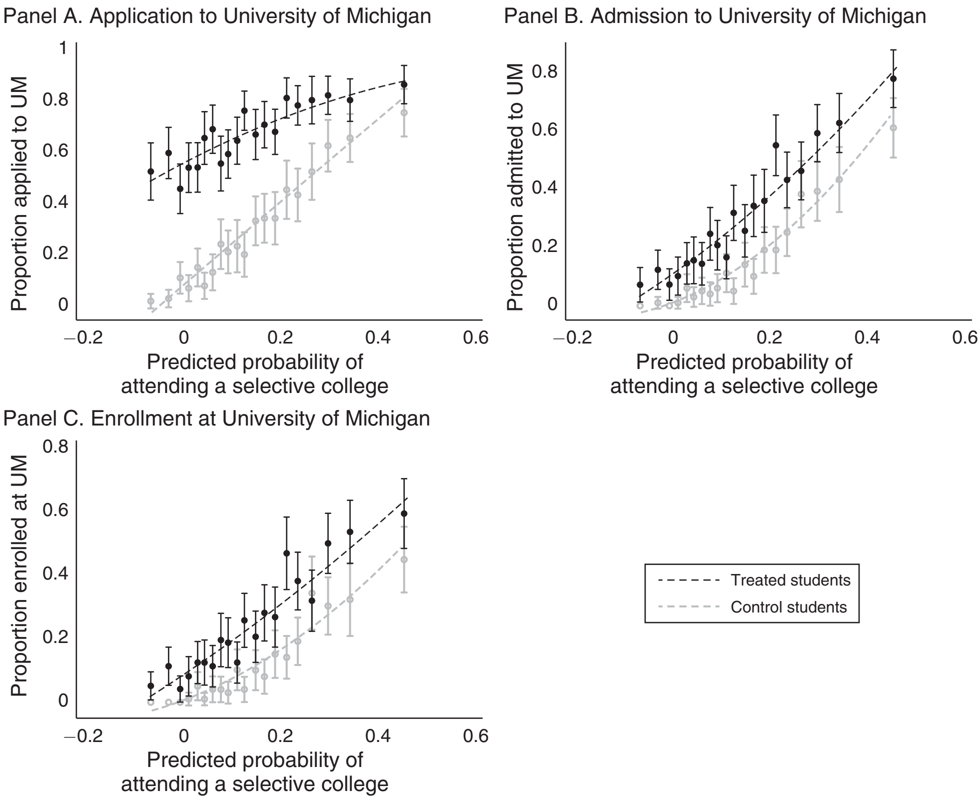

Figure 5. Estimated Effect of HAIL Scholarship by Predicted Probability of Selective College Attendance, First and Second HAIL Cohorts

Notes: This analysis is done at the student level. Selective college attendance is predicted from a regression that included race, gender, ACT, GPA, urbanicity and region of high school, number of eligible students in school, and persistence of economic disadvantage. Graphs are binned scatterplots where students are grouped into 20 roughly equally sized bins, by treatment status. The *y*-values represent within-bin means; *x*-values represent the mean of the index by ventile. Ninety-five percent confidence intervals shown. Standard errors clustered at the school level.

Sources: Michigan administrative data and University of Michigan Office of Enrollment Management data

on extracurricular activities, for example. By the fall of each cohort's senior year we receive test scores from junior year and GPA from freshman and sophomore years. But since grades in junior and senior year weigh heavily in admissions, students who look like marginal admits at the end of sophomore year may be inadmissible by senior year. The opposite is also true: students with poor grades at the end of sophomore year may have pulled them up by senior year and be good prospects for admission. In future work, we plan to experimentally vary the criteria used for targeting HAIL so the university has empirical evidence on how these choices affect the composition of applicants, admits, and enrolled students.

D. *Did the Intervention Poach Students from Other Selective Colleges?*

The HAIL intervention may have increased enrollment at University of Michigan by simply diverting students from other selective schools, such as Berkeley or

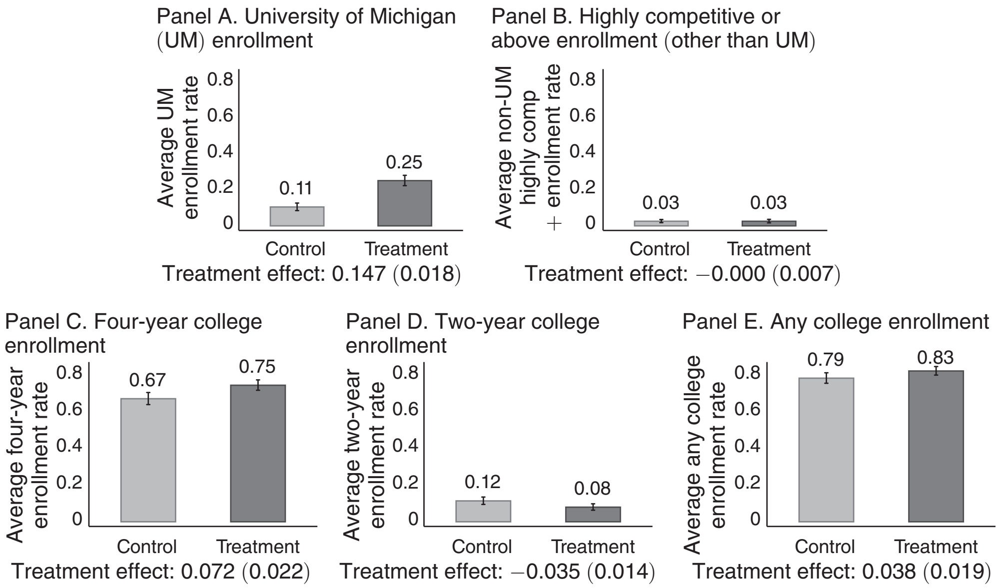

Figure 6. Estimated Effect of HAIL Scholarship on College Choice, First and Second HAIL Cohorts

Notes: All analyses done at the school-year-level. Ninety-five percent confidence intervals shown based on standard errors clustered at the school level. Enrollment measured at the first institution attended in the fall following expected high school graduation. Enrollment unconditional on any college enrollment. Treatment effects estimated from a regression of the outcome on an indicator for treatment status and strata dummies. Robust standard errors clustered at the school level reported in parentheses.

Source: Michigan administrative data

Harvard. This would imply much smaller welfare effects than the estimates shown so far have suggested. We turn to data from the Michigan Department of Education (2020b) to examine the effect of the treatment on enrollment at other colleges.[35]

We find no diversion from colleges at least as selective as the University of Michigan (Figure 6 and online Appendix Table 14). The offer of the HAIL scholarship neither discouraged, nor encouraged students from enrolling at other highly selective institutions.[36]

Students in the treatment group were 3.8 percentage points more likely to attend any postsecondary institution than those in the control group. That is, roughly one-quarter of the increase in enrollment at the University of Michigan is driven by students who would not have attended *any* college in the absence of the treatment. We did not anticipate this result; it seemed unlikely that students this well prepared would be on the margin of not attending college.

Additionally, the offer of HAIL increased the share of students enrolling at any four-year college (7.2 percentage points) and decreased the share enrolling at two-year colleges (3.5 percentage points). Together, these results show that nearly

[35] We have no application or admissions information for schools other than the University of Michigan.

[36] This estimate (which uses Michigan Department of Education 2020b data) and the previously discussed estimate (based on University of Michigan Office of Enrollment Management 2020a data, Figure 4) are nearly identical: 14.7 versus 15.1 percentage points. The minor difference is attributable to differences in the dates on which NSC and University of Michigan record enrollment.

one-half of HAIL's effect on enrollment is diversion from two-year colleges and non-attendance. The other half is diversion from four-year colleges that are less selective than the University of Michigan.

These results are consistent with responses from focus groups held among students from the treatment group who enrolled at the University of Michigan. Of the 15 students interviewed in the focus groups, 12 had no intention of applying to the University of Michigan before the intervention. Typical among the target institutions mentioned by students were regional, four-year institutions such as Grand Valley State, Ferris State, Central Michigan University, Wayne State University, and Eastern Michigan University. One student in the focus group had contemplated a two-year college, while another explained that they "didn't count on going to college at all until I got the packet" (Glasener et al. 2018, and unpublished focus group transcripts).

E. *Whose Behavior Was Changed by the Intervention?*

To gain some insight into the mechanisms through which HAIL affected decision-making, we next examine the characteristics of students whose behavior was changed by the intervention.

Complier Characteristics.—One way to frame our intervention is that it randomly assigns students to apply to the University of Michigan, and there is imperfect compliance. In this framework, treatment assignment is an instrumental variable (IV) for applying. We follow Imbens and Rubin (1997) in analyzing the characteristics of the compliers, those students whose behavior was changed by the intervention (see online Appendix Section C for methodological details).

We compare the compliers to the always-takers (who apply even in the absence of the treatment) and the never-takers (who do not apply even if assigned to treatment). These latter two groups comprise the inframarginal students, whose behavior is unmoved by the intervention. The always-takers are firmly committed to applying, while the never-takers are firmly committed to not applying, with "commitment" reflecting the reduced-form effect of preferences and constraints.

We summarize the salient differences between the compliers, always-takers, and never-takers using the predicted index discussed in the previous section. We find that 23 percent of always-takers are predicted to attend a highly competitive college, compared to just 10 percent of compliers and never-takers.

In observable characteristics, the compliers differ markedly from always-takers and more closely resemble the never-takers (Table 3). Compliers live further away from University of Michigan than the always-takers, as they are disproportionately concentrated in the Upper Peninsula and the West Central regions. Reflecting the demographics of those regions, compliers are more likely to be White and to attend rural schools with few low-income, high-achieving peers.

The compliers, as well as the never-takers, were considerably less likely than always-takers to be known to University of Michigan admissions before the HAIL intervention. Like many colleges, the University of Michigan compiles lists of prospective applicants to target for recruitment. The admissions office collects names at college fairs, solicits e-mail addresses at its Website, and purchases lists of high-scoring students from the SAT and ACT. Presence on the list therefore reflects the

Table 3—Selected Characteristics of Compliance Subpopulations

	Full sample	Always-takers	Never-takers	Compliers	Compliers/full sample
Share of students in each population	1	0.3	0.32	0.38	
	Mean of each characteristic for each population				
Upper Peninsula	0.11	0.05	0.13	0.12	1.16
West Central	0.42	0.33	0.44	0.48	1.13
Southeast	0.47	0.62	0.42	0.4	0.85
Suburban	0.46	0.51	0.45	0.42	0.92
City	0.14	0.26	0.09	0.07	0.55
Town or rural	0.41	0.23	0.46	0.51	1.24
Number of 11th grade students in school	249	277	249	228	0.92
Number of HAIL students in school	6.88	8.07	7.04	5.81	0.84
Female	0.58	0.51	0.61	0.61	1.05
White (non-Hispanic)	0.77	0.61	0.81	0.85	1.11
Asian	0.08	0.16	0.05	0.04	0.56
Black (non-Hispanic)	0.08	0.14	0.07	0.05	0.63
Hispanic	0.06	0.07	0.06	0.04	0.63
American Indian or Native Hawaiian	0.01	0.02	0.01	0.01	0.95
Free lunch eligible	0.7	0.75	0.67	0.69	0.98
Reduced-price lunch eligible	0.3	0.25	0.33	0.31	1.04
SAT score (or equivalent)	1263	1298	1245	1251	0.99
GPA	3.82	3.85	3.8	3.81	1
New to University of Michigan admissions office	0.43	0.16	0.60	0.50	1.16
Predicted probability of highly selective college attendance	0.14	0.23	0.10	0.10	0.7

Notes: This analysis is done at the student level. Row 1 shows the share of each compliance group in the sample. The remaining rows show the means of each student or school characteristic across the different subpopulations. The final column displays the ratio of compliers to full sample means for each characteristic à la Angrist and Pischke (2009) for easy comparison of where compliers differ most from the sample as a whole. Each of these statistics is calculated with information about observable always-takers and never-takers using the methods from Imbens and Rubin (1997) and formally extended by Marbach and Hangartner (2020). See online Appendix Section C for more details on these calculations.

Sources: Michigan administrative data and University of Michigan Office of Enrollment Management data

reduced-form effect of connection to the traditional admissions apparatus, expressed interest in the University of Michigan, and academic achievement. About one-half of our sample students were already listed in this University database, while the other half were not. In subgroup analyses that compare treatment effects between these groups (see online Appendix Table 10), we find similar point estimates, but far lower control means for those previously unknown to University of Michigan.

Heterogeneity by Geography and Demographics.—We next explore heterogeneity in the effects of the intervention by specific characteristics of students and schools. We show differences in HAIL's effects by geography, income, race/ethnicity, and gender.

HAIL tended to equalize student outcomes across region and urbanicity, with the largest treatment effects in the regions with the lowest control means (see Table 4 for regression estimates and online Appendix Figures 4 and 5 for treatment and control means). HAIL reduced the gap in enrollment rates between urban and rural schools by one-half, from 14 percentage points in the control group to 7.6 percentage points in the treatment group. The outsized impact of the treatment on students in more rural areas of the state as well as locales farther from University of Michigan is consistent with the treatment offsetting student isolation.

Table 4—Estimated Effect of HAIL Scholarship on University of Michigan Application, Admission, and Enrollment by Geography, First and Second HAIL Cohorts

	Panel A. Region				*Panel B. Urbanicity*			
	Southeast	West Central	Upper Peninsula	p-value, F-test of treatment-by-region interactions	Suburb	City	Town or rural	p-value, F-test of treatment-by-urbanicity interactions
Applied	0.382	0.467	0.390	0.136	0.390	0.293	0.482	0.008
	(0.032)	(0.031)	(0.054)		(0.031)	(0.061)	(0.029)	
	[0.364]	[0.200]	[0.156]		[0.336]	[0.464]	[0.159]	
		{0.057}	{0.900}			{0.157}	{0.032}	
Admitted	0.160	0.184	0.183	0.843	0.156	0.048	0.225	0.029
	(0.034)	(0.029)	(0.046)		(0.030)	(0.068)	(0.027)	
	[0.202]	[0.116]	[0.105]		[0.164]	[0.319]	[0.097]	
		{0.577}	{0.685}			{0.150}	{0.088}	
Enrolled	0.145	0.150	0.170	0.902	0.131	0.114	0.181	0.338
	(0.031)	(0.025)	(0.047)		(0.029)	(0.063)	(0.025)	
	[0.167]	[0.085]	[0.080]		[0.140]	[0.221]	[0.078]	
		{0.890}	{0.652}			{0.804}	{0.194}	
Number of school-years	408	474	144		359	118	549	
Number of students	1,848	1,646	416		1,784	530	1,596	

Notes: All analyses done at the school-year level. For each panel, treatment effects are from a single regression of the outcome on treatment status and strata dummies, fully interacted with subgroup indicators. Robust standard errors clustered at the school level reported in parentheses. Control mean for subgroup in brackets. p-value from test of subgroup compared to reference subgroup (Southeast or suburban schools) in curly brackets. F-test jointly tests the significance of the treatment-by-subgroup interactions. Application, admission and enrollment measured in the summer and fall following expected high school graduation. Admission and enrollment are unconditional on application.

Sources: Michigan administrative data and University of Michigan Office of Enrollment Management data

Though all students in our sample are from low-income households, they vary in the degree of their economic disadvantage. We might expect larger treatment effects among the most disadvantaged, who face stricter constraints than their peers.

While we lack income data, we can distinguish between students who received a free meal in school (whose family income is below 130 percent of the federal poverty line) and those who received a reduced-price meal (who have family income between 130 and 185 percent of the federal poverty line). We also group students by whether they were eligible for free or reduced-price lunch in all of their pre-treatment high school years (grades 9 through 11) or only for some of their high school years.[37] Michelmore and Dynarski (2017) show that students who spend more years eligible for subsidized school meals come from families with the lowest incomes.

Table 5 shows treatment effects by these two proxy measures of income. We find weak evidence that the intervention had a larger effect for more disadvantaged students. Though the estimated effects are statistically indistinguishable, the effects for the more disadvantaged students, those disadvantaged for all of high school, are consistently larger in magnitude than for their more advantaged peers.

[37] The majority of students in our sample received a free lunch (70 percent) compared to a reduced-price lunch (30 percent). Eighty-four percent of students in our sample qualified as economically disadvantaged for every year we observed them, while the remaining 16 percent were disadvantaged for only some of their high school years.

Table 5—Estimated Effect of HAIL Scholarship on University of Michigan Application, Admission, and Enrollment by Economic Status, First and Second HAIL Cohorts

	Panel A. Free or reduced-price lunch eligibility			*Panel B. Persistence of economic disadvantage*		
	Free lunch	Reduced-price	*p*-value, difference	Always disadvantaged	Sometimes disadvantaged	*p*-value, difference
Applied	0.421	0.417	0.921	0.422	0.400	0.619
	(0.024)	(0.033)		(0.023)	(0.043)	
	[0.270]	[0.245]		[0.259]	[0.302]	
Admitted	0.171	0.146	0.456	0.176	0.151	0.541
	(0.022)	(0.029)		(0.022)	(0.038)	
	[0.151]	[0.146]		[0.149]	[0.167]	
Enrolled	0.147	0.115	0.308	0.153	0.139	0.722
	(0.020)	(0.026)		(0.020)	(0.036)	
	[0.116]	[0.118]		[0.118]	[0.130]	
Number of school-years	923	607		982	425	
Number of students	2,748	1,162		3,268	642	

Notes: All analyses done at the school-year level. For each panel, treatment effects are from a single regression of school-subgroup-level outcome rate on treatment status and strata dummies, fully interacted with an indicator for subgroup. Robust standard errors clustered at the school level reported in parentheses. Control mean for subgroup in brackets. UM application, admission, and enrollment measured in the summer and fall following expected high school graduation. Admission and enrollment are unconditional on application. In Panel A, eligibility is measured in eleventh grade. In Panel B, "always disadvantaged" is defined as being eligible for free or reduced-price lunch every (observed) year of high school through 11th grade (including repeated grades).

Sources: Michigan administrative data and University of Michigan Office of Enrollment Management data

We find substantial differences in treatment effects across race and ethnic groups (see Table 6 and online Appendix Figure 8). This closely tracks the geographic variation in effects and is in fact difficult to distinguish from it. In Michigan, Black and Hispanic students are concentrated in the cities, while the rural areas are largely White. We have insufficient support in our sample to precisely estimate racial effects within region (or regional effects within race).

The intervention reduced racial and ethnic inequality in applications, admission, and enrollment at University of Michigan. Absent the intervention, students of Black, Asian, and Hispanic descent were far more likely to apply to and attend the University of Michigan than White, non-Hispanic students. For example, 21 percent of White students in the control group applied to Michigan, substantially lower than the rate for Asian (60 percent), Black (48 percent), and Hispanic students (40 percent). The pattern is similar for admission and enrollment rates.

These patterns reflect the concentration of Black, Asian, and Hispanic students in urban areas of Southeast Michigan, which are closer to the University of Michigan. The rural schools in the more distant parts of the state, which have the lowest application rates, are overwhelmingly White.

A consistent pattern in Table 6 is that the treatment effects are inversely related to control-group means. For example, HAIL's effect on application rates is substantially larger for White students (44 percentage points) than it is for Asian, Black, and Hispanic students (23, 29, and 22 percentage points, respectively).

Finally, we examine differences by gender (see Table 6). Men are, compared to women, more confident in their skills and prefer competitive environments (Niederle

Table 6—Estimated Effect of HAIL Scholarship on University of Michigan Application, Admission, and Enrollment by Student Gender and Race, First and Second HAIL Cohorts

	Panel A. Gender		*Panel B. Race/Ethnicity*				
	Women	Men	White	Asian	Black	Hispanic	p value, F-test of treatment-by-race/ethnicity interactions
Applied	0.424	0.403	0.445	0.232	0.292	0.221	0.000
	(0.025)	(0.029)	(0.023)	(0.060)	(0.057)	(0.079)	
	[0.239]	[0.286]	[0.210]	[0.601]	[0.478]	[0.405]	
		{0.548}		{0.001}	{0.011}	{0.006}	
Admitted	0.190	0.143	0.185	0.179	0.106	0.036	0.140
	(0.024)	(0.025)	(0.020)	(0.065)	(0.060)	(0.071)	
	[0.143]	[0.139]	[0.116]	[0.279]	[0.283]	[0.265]	
		{0.155}		{0.929}	{0.199}	{0.040}	
Enrolled	0.164	0.121	0.157	0.139	0.063	0.088	0.341
	(0.022)	(0.023)	(0.019)	(0.057)	(0.054)	(0.067)	
	[0.115]	[0.105]	[0.091]	[0.219]	[0.234]	[0.198]	
		{0.150}		{0.765}	{0.095}	{0.318}	
Number of school-years	855	729	929	174	206	148	
Number of students	2,273	1,637	3,002	310	330	218	

Notes: All analyses done at the school-year level. For each panel, treatment effects are from a single regression of school-subgroup-level outcome rate on treatment status and strata dummies, fully interacted with subgroup indicators. Robust standard errors clustered at the school level reported in parentheses. Control mean for subgroup in square brackets. p-value from test of subgroup compared to reference subgroup (women or White students) in curly brackets. F-test jointly tests the significance of the treatment-by-race/ethnicity-category interactions. UM application, admission, and enrollment measured in the summer and fall following expected high school graduation. Admission and enrollment are unconditional on application.

Sources: Michigan administrative data and University of Michigan Office of Enrollment Management data

and Vesterlund 2007). In the control group, women were 5 percentage points *less* likely to apply than men (24 versus 29 percent) but slightly *more* likely to enroll (12 versus 11 percent), suggesting that, absent the treatment, female applicants are more qualified than male applicants. The HAIL treatment narrowed the gender gap in application from 5 percentage points to three (66 percent of women and 69 percent of men applied to University of Michigan from the treatment group) and widened the female advantage in enrollment from 1 percentage point to six. These results are consistent with HAIL compensating for women's lower levels of confidence about applying to a highly selective school.

Building on the results by region and urbanicity, we additionally test how HAIL affected isolated students by estimating variation in the treatment effects by the number of HAIL-eligible students in the school (see online Appendix Table 9 and online Appendix Figure 6).[38] In assigning schools to treatment, we stratified on this characteristic because we hypothesized that the number of similarly high-achieving but low-income peers in a school would affect students' baseline propensity to apply to a selective school. We estimate heterogeneity by interacting the treatment indicator with a linear term for the number of HAIL students in each school.

[38] The number of HAIL-eligible students in each high school varies by our experimental cohort.

The results suggest isolation plays a role in undermatch: treatment effects are largest at schools with the fewest HAIL-eligible students. For a school with one HAIL-eligible student, the treatment effect on application is 46.6 percentage points. For a school with five HAIL-eligible students, the effect is 40.1 percentage points. We observe a similar pattern on the enrollment margin.[39] This pattern suggests that the HAIL scholarship had slightly larger effects on students who were more isolated from other high-achieving, low-income students.

VI. Welfare Effects and Unintended Consequences

The results discussed thus far illustrate HAIL's effect on sample students' college choices. In this section, we examine the implications of these behavioral responses for student and social welfare. We examine whether students induced to enroll persisted in college, how their financial aid packages compared to other low-income students, and whether HAIL had any spillover effects.

A. *Did Students Induced to Attend Quickly Drop Out?*

Did those induced by HAIL into a highly selective college persist in college, or quickly drop out? Before undermatch was a hot topic, *overmatch* was a key concern, with some worried that disadvantaged students induced to attend highly selective schools would not be able to handle the academic competition. But recent research suggests that students are more likely to graduate if they attend the best school they can get into (Hoekstra 2009, Zimmerman 2014, Dillon and Smith 2018).

While we cannot yet observe graduation, we do have data on attendance in two consecutive years for the first cohort of students, which allows us to examine persistence in college. We find that the effects of HAIL persist into the second year (Table 7). Students offered the HAIL scholarship are 12.8 percentage points more likely than controls to be enrolled at the University of Michigan for two years. The two-year effect is 87 percent $(= 12.8/14.7)$ of the one-year effect.

On all other measures, we find *larger* treatment effects over a two-year horizon than over one year. Students offered HAIL are 11 percentage points more likely to be enrolled in a four-year college for two years (the one-year effect is 9 percentage points), and they are 8 percentage points more likely than controls to enroll in *any college* for two consecutive years (the one-year effect is 4 percentage points). This is partly driven by HAIL getting students into college in the first place (the increase of 4 percentage points seen in Figure 6 and online Appendix Table 14) and partly by inframarginal college students attending a more selective college with a higher retention rate.[40] This is consistent with the hypothesis that students induced into

[39] Heterogeneity by baseline high-school level UM enrollment rate presents a similar pattern: Treatment effects are largest in schools that previously had no students enroll at the University of Michigan; see online Appendix Table 9.

[40] Persistence effects are largest in suburban and rural areas of the state, and for female students (see online Appendix Table 17). Persistence effects by race/ethnicity are consistent with the initial enrollment results: we find larger effects among White and Asian students, while effects for other racial minorities are noisy and often not significant. Control group means were also higher among these other minorities, which again points to the treatment having the largest impact on students who were otherwise less likely to attend a highly selective school.

Table 7—Estimated Effect of HAIL Scholarship on College Enrollment and Persistence, First HAIL Cohort

	Attended fall following high school graduation		Attended two consecutive falls following high school graduation	
College attended	Treatment effect	Control mean	Treatment effect	Control mean
University of Michigan (UM)	0.147 (0.022)	0.104	0.128 (0.022)	0.102
Highly competitive or above other than UM	0.006 (0.010)	0.026	0.006 (0.010)	0.024
Four-year	0.091 (0.028)	0.651	0.109 (0.029)	0.557
Two-year	−0.034 (0.019)	0.127	−0.013 (0.016)	0.078
Any	0.057 (0.025)	0.779	0.079 (0.027)	0.683
Number of school-years		529		
Number of students		2,108		

Notes: All analyses done at the school-year level. Coefficients are from regressions of outcome on treatment status and strata dummies. Robust standard errors clustered at the school level reported in parentheses. Enrollment is measured at the first college attended in the two falls following expected high school graduation and is unconditional on any college enrollment.

Source: Michigan administrative data

more selective schools, with better-prepared peers and more resources, are more likely to remain in school and graduate.

B. *College Completion Predictions*

While we cannot yet observe college completion rates, we can, following Athey et al. (2019), employ a surrogate index technique to predict the effect of HAIL on college completion. Using a previous cohort of low-income, high-achieving students in Michigan, we first predict the likelihood of completing college based on a vector of intermediate outcomes (such as enrolling in a highly competitive institution) and a vector of student characteristics. We then use the coefficients from this regression to predict college completion rates for the HAIL sample and regress the predicted completion rate on an indicator for whether the school was in the treatment or control group.[41]

Using the surrogate index technique, we predict the HAIL intervention increases the share of students earning a bachelor's degree within four years by 7.9 percentage points (see Table 8), with a 95 percent confidence interval ranging from 4.8 to 11 percentage points. We predict HAIL will increase five-year completion by 7.4 percentage points, with a 95 percent confidence interval ranging between 3.7 and 11.1 percentage points. These predictions are within range of other estimates in the literature, which we discuss in more detail in the conclusion.[42]

[41] See online Appendix Section D for more details on how we constructed the index.

[42] As a validation exercise, we also used the surrogate index method to predict outcomes that we already observe for our first HAIL cohort: persisting at a highly competitive institution for two consecutive falls, persisting at a four-year institution for two consecutive falls, and persisting at any institution for two consecutive falls. For all of the outcomes we test, the predicted point estimates are within the confidence interval of the actual observed

Table 8—Predicted Effect of HAIL Scholarship on Persistence and College Completion, First HAIL Cohort

	Observed treatment effect (Table 7)	Predicted treatment effect	Observed control mean (Table 7)	Predicted control mean
Bachelor's degree within 4 years	n/a	0.079 (0.016)	n/a	0.304
Bachelor's degree within 5 years	n/a	0.074 (0.019)	n/a	0.496
Two-year persistence at:				
University of Michigan	0.128 (0.022)	0.104 (0.016)	0.102	0.087
Four-year institution	0.109 (0.029)	0.088 (0.026)	0.557	0.574
Any institution	0.079 (0.027)	0.062 (0.023)	0.683	0.689
Number of school-years	529		529	
Number of students	2,108		2,108	

Notes: All analyses conducted at the school-year level. Predicted likelihood of completing a bachelor's degree based on a previous cohort of Michigan public school seniors in the two years prior to the HAIL scholarship intervention (see online Appendix Section D for details on how this was constructed). Coefficients are from regressions of outcome on treatment status and strata dummies. Robust standard errors adjusted for using a predicted value and clustered at the school-level in parentheses.

Source: Michigan administrative data

C. *How Costly Was the Intervention?*

The cost of printing and mailing the intervention packages was low, approximately \$10 per student.[43] Beyond the cost of the packet, did the promise of free tuition cost the university more in financial aid than they would otherwise provide low-income students? In analyzing prior cohorts of low-income students enrolled at the University of Michigan, we found that 90 percent received at least a full-tuition scholarship. We expected that, for the vast majority of students in our sample, the HAIL scholarship would guarantee aid for which students were already eligible.

Indeed, we find no significant differences between the financial aid packages of students in the treatment and control groups enrolled at the University of Michigan (see Table 9). Since HAIL induced students to enroll, we do not interpret these results in any causal way, but provide this information to illustrate that HAIL students were treated identically (in terms of their financial aid packages) as other low-income students enrolled at the University of Michigan.

Financial aid applications contain detailed data on family finances. Students from the treatment and control groups came from families with similar incomes (\$36,000), and similar expected family contributions (just over \$3,000). Both treatment and control students received, on average, around \$24,000 in grants and scholarships in their first year, and the vast majority of that came from university grants. Approximately 85 percent of students received Pell grants, and the average amount

treatment effect, and in all cases the predicted treatment effects are approximately 80 percent the magnitude of the observed treatment effect (see Table 8).

[43] This includes the costs of producing the packets, the mailing costs, and the administrative costs of designing the packets.

Table 9—Financial Aid for HAIL Treatment and Control Students Enrolled at the University of Michigan, by Year of College Enrollment (Non-Experimental Results), First and Second HAIL Cohorts

	First Year			Second Year		
	Mean			Mean		
	Control	Treated	p-value	Control	Treated	p-value
Adjusted gross income (parent)	\$35,553 (2,619)	\$36,029 (1,395)	0.820	\$37,144 (2,722)	\$36,261 (1,501)	0.841
Adjusted gross income (student, dependent)	\$674 (112)	\$1,001 (93)	0.039	\$947 (129)	\$1,379 (118)	0.016
Expected family contribution	\$3,312 (428)	\$3,306 (284)	0.995	\$3,621 (501)	\$3,171 (270)	0.433
Total grants + scholarships	\$24,566 (518)	\$23,907 (253)	0.268	\$25,413 (555)	\$24,525 (302)	0.173
University of Michigan (UM) grants	\$19,431 (426)	\$18,977 (164)	0.349	\$20,129 (434)	\$19,559 (202)	0.250
Pell Grant	\$4,537 (149)	\$4,299 (114)	0.203	\$4,516 (170)	\$4,287 (122)	0.293
State grants	\$40 (22)	\$31 (13)	0.634	\$142 (24)	\$88 (13)	0.022
Federal Supplemental Educational Opportunity Grants	\$557 (47)	\$600 (40)	0.519	\$626 (53)	\$592 (36)	0.582
Loans	\$1,342 (203)	\$1,752 (160)	0.138	\$1,543 (228)	\$1,946 (164)	0.208
Work study	\$1,144 (86)	\$1,625 (63)	0.000	\$1,305 (82)	\$1,482 (65)	0.107
Number of students in the study	1,978	1,932	3,910	1,978	1,932	3,910
Number of students enrolled at UM	238	480	718	235	450	685
Number of students with FAFSA data	234	478	712	228	440	668
Number of students with data on aid awarded	236	480	716	232	450	682

Notes: Analyses done at the student level, for students enrolled at UM and with financial aid information available. First Year refers to the first year of college enrollment, i.e., the academic year following high school graduation. p-values are from a t-test of the coefficient on treatment status from a regression of the characteristic on treatment and strata dummies. Standard errors are clustered at the school level.

Sources: Michigan administrative data and University of Michigan Office of Enrollment Management data

was over \$4,000. Treated students were slightly more likely to receive work study, generating differences in their average work study amounts. (Treated students had slightly higher earnings than those in the control group, of about \$300 in their first year of college.) These comparisons are quite similar in the first and second year of enrollment. Overall, Table 9 suggests that HAIL does not cost the university more in terms of financial aid than they would otherwise provide low-income students.

D. *Did the Intervention Discourage Any Students?*

There are at least two ways in which the intervention could have harmed some students.

First, students in the treatment group who applied but were rejected from the University of Michigan may have been discouraged from applying to or attending other colleges. Here, the key question is whether they would have been better off if they had not applied at all than to have applied and been rejected. One scenario is that students are so encouraged by the mailings that they focus all of their application efforts on University of Michigan, to the exclusion of other colleges. This would tend to reduce the rate of college attendance in the treatment group, relative to the control group. While we cannot use the experimental design to address this question directly since we do not have random variation in admission among applicants, we do find that the treatment increased the likelihood of attending *any* college by 4 percentage points and the likelihood of attending a four-year college by 7 percentage points (see Figure 6). If there were any discouragement effects they were more than offset by the encouragement effects of the intervention.

Second, the HAIL intervention may have affected the college choices of high school classmates who were ineligible for the HAIL scholarship (those who failed to meet the income or academic criteria). The sign of any spillover effect is theoretically ambiguous. Seeing a peer offered the HAIL scholarship may suggest to a student that she is not University of Michigan material, decreasing the likelihood of application. On the other hand, seeing a peer offered the HAIL scholarship may make the University of Michigan seem more accessible to students (or adults around them), thereby increasing the likelihood of application. Finally, the University of Michigan may have informal quotas for each school, which would mechanically constrain admissions for classmates.

To check for spillover effects, we replicate our analysis among students not eligible for HAIL, with the treatment dummy indicating that their school is in the HAIL treatment group. We find no evidence of negative (or positive) spillover effects on students attending HAIL-treated schools who did not receive the offer (see online Appendix Table 18). This result is not entirely surprising, since HAIL students make up a small fraction of the total freshman class size. Each year, HAIL induced approximately 150 additional students to enroll, while the freshman class at the University of Michigan is over 6,000 students.

VII. Conclusion

We close the paper with the statistics that motivated it: gaps in college choice between low-income students and their higher-income peers in Michigan (Figure 7). HAIL closed by half the income gap in college attendance among high-achieving students: the college attendance rate is 88 percent among upper-income students, 85 percent among low-income students in the treatment group, and 81 percent among low-income students in the control group.

HAIL also narrowed, eliminated, and even *reversed* income gaps in college selectivity. The intervention shifted students away from two-year and less selective four-year colleges (Figure 6). The gap in attending an institution considered "selective" or above was reduced from 12 percentage points to 4 percentage points, and the income gap in attending an institution considered "very selective" or above was eliminated. Low-income, high-achieving students offered HAIL are *more likely* to attend a university at least as selective as the University of Michigan than their higher-income peers: 26 versus 20 percent, respectively. We find no evidence that HAIL diverted students from other highly selective institutions. Finally, these effects

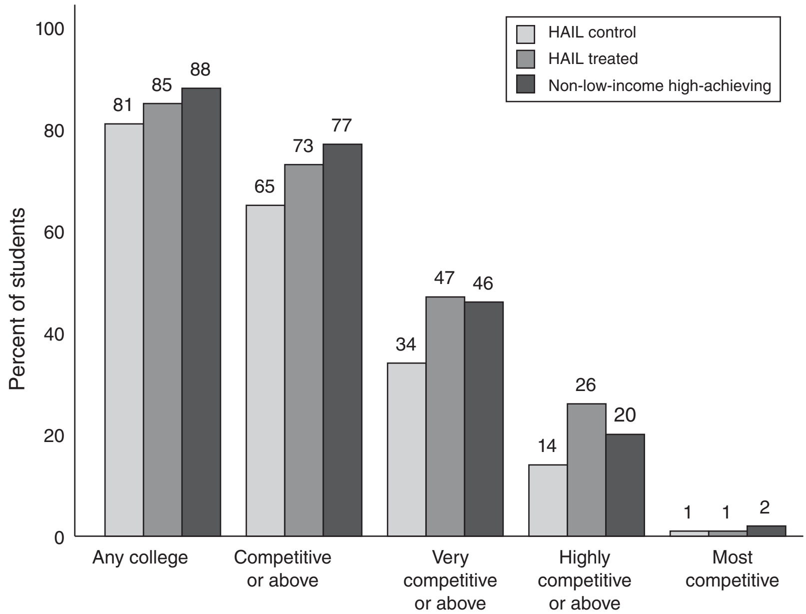

Figure 7. Selectivity of Colleges Attended by High-Achieving Michigan Students, by Income and HAIL Treatment Status, First and Second HAIL Cohorts

Notes: Sample is eleventh grade students in Michigan public schools in 2015 and 2016 who meet HAIL GPA and ACT/SAT criteria. College enrollment measured at first institution attended in fall following expected high school graduation. Low-income means eligible for free or reduced-price lunch in eleventh grade. Selectivity categories from Barron's selectivity index.

Source: Michigan administrative data

have lasted: students offered the HAIL scholarship have persisted in college at substantially higher rates than students in the control group.

These results indicate that a low-cost, low-touch intervention can strongly affect student application and enrollment at selective colleges. This contrasts with the conclusion of Carrell and Sacerdote (2017) that only high-touch, "boots on the ground" interventions can have large effects on students' decisions to apply to and attend college.

The 15 percentage point effect on enrollment that we uncover is much larger than those of most previous interventions with similar goals and approaches. Two studies, Hoxby and Turner (2013) and Gurantz et al. (2019), provided low-income, high-achieving students with personalized information about their financial aid eligibility. The first intervention increased the share of students enrolled in a selective college by 5 percentage points (from a control mean of 29 percent), while the second found zero effect. In Michigan, Hyman (2020) sent information about college quality and costs to high school students scoring in the top half of the ACT distribution, with no effect. In Texas, Bergman, Denning, and Manoli (2019) provided information about tax benefits for college expenses to both applicants and currently enrolled students, with no effect.

Past interventions that provided more intensive, "hands-on" guidance have produced more consistently positive results, though not as large as those induced by

HAIL. In Ontario, an intervention studied by Oreopoulos and Ford (2019) helped high school students with college applications, yielding a 5 percentage point increase in college enrollment (from a control mean of 53 percent). In a series of experiments, Carrell and Sacerdote (2017) provided mentors and college counseling to low-income students in New Hampshire and Vermont, increasing college enrollment by 6 percentage points (from a control mean of 44 percent). An intervention designed by Bettinger et al. (2012) helped low-income families in filling out the FAFSA, yielding a 9.4 percentage point increase in full-time college enrollment (from a mean of 34 percent).

It is still too early to measure the effect of the HAIL intervention on college completion. Based on the enrollment effects so far, we predict (see Section VIB) that HAIL will increase the likelihood of earning a bachelor's degree by 7 percentage points. There is no previous experimental evidence of the effect of inducing students to attend a more selective college. Most closely related are two studies that use a regression-discontinuity design to examine the effect of just qualifying for admission to a public, four-year college. In these settings, the counterfactual is no college, or enrollment at a two-year college. Zimmerman (2014) finds that those who just qualify for admission to Florida International University are 5.7 percentage points more likely to earn a bachelor's degree. Goodman, Hurwitz, and Smith (2017) find that low-income students who just qualify for admission to the Georgia State University System (comprised of all the public, four-year colleges in the state) are 2 percentage points more likely to earn a bachelor's degree.

How might HAIL replicate in other settings? HAIL is essentially extremely effective marketing. From the perspective of a school aiming to recruit students, it is easily adaptable and replicable. But the social welfare effects of such a campaign depend crucially on who is targeted, the quality and cost of the recruiting school, and the students' choice set.

In some settings, the flagship public university will be a worse choice than the alternatives available to high-achieving students. In Massachusetts, a free-tuition scholarship for high-achieving students diverted students from the state's private colleges. As shown by Cohodes and Goodman (2014), the program effectively induced students to attend colleges where they were worse off, and reduced the share of students graduating with a bachelor's degree. In our setting, the University of Michigan dominates other options in the state for high-achieving, low-income students. Its spending per pupil and graduation rate are higher than that of any other college in the state and it also has the most generous aid for low-income students (see Table 1).

Schools and states considering a HAIL-like intervention should carefully consider students' choice sets before launching their own program. HAIL was designed for the Michigan setting, but the behavioral principles that undergird it can be adapted for a different environment. For example, in some states there are several selective schools that would be an affordable, academic match for high-achieving, low-income students. This set of colleges could jointly deliver to low-income students an early guarantee of tuition and fees.

The behavioral patterns uncovered by this study have broad implications for policy. People frequently make consequential decisions in complex, uncertain environments. Our study adds to a body of evidence showing that the design of those environments can profoundly shape decisions (Madrian and Shea 2001, Herd and Moynihan 2018, Pallais 2015, Marx and Turner 2019). Like many means-tested programs, the student aid system in the United States is rife with detailed rules and extensive paperwork. Many of these rules are the accidental product of well-intentioned actors.[44] The broadest conclusion to be drawn is that the "last mile" of policy implementation can have serious distributional consequences. The design of a user interface, the length of a form, and the timing of information delivery can have profound effects on behavior. Research suggests that this is especially true for poor people (Mullainathan and Shafir 2013). But even among white-collar professionals, details of program administration can affect decisions as consequential as whether to save for retirement.[45]

More narrowly, our results inform the various "free college" policies that have been widely discussed in state legislatures, in presidential campaigns, and on Capitol Hill. Critics have argued that these policies cannot help low-income students, whose tuition costs at many colleges (including virtually all community colleges) are already covered by need-based aid. But this is exactly what HAIL does: guarantee free tuition for students who, in expectation, will eventually be deemed eligible for aid that more than covers tuition.

Our findings indicate that the details of implementation will be crucial to the success of these policies. Free-college programs can be designed with required aid forms and back-loaded information about eligibility, which is what our control students experienced. Alternatively, they can provide an early, unconditional guarantee of tuition, which is what our treatment students were offered. These seemingly minor differences in policy design can have profound effects on behavior.

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[44] A legislator may, for example, sponsor a provision to extend additional aid to homeless students. Depending on how this is implemented, this could further add to program complexity. In 2007, Congress passed legislation guaranteeing aid eligibility to homeless students. The Department of Education implemented this directive by adding three lengthy, legalistic questions to the FAFSA that probe for homeless status.

[45] Making employee participation in a company 401(k) opt-out rather than opt-in dramatically increases savings rates (Madrian and Shea 2001).

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