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Showing high-achieving college applicants past admissions outcomes increases undermatching

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More than 40% of US high school students have access to Naviance, a proprietary tool designed to guide college search and application decisions. The tool displays, for individual colleges, the standardized test scores, grade-point averages, and admissions outcomes of past applicants from a student's high school, so long as a sufficient number of students from previous cohorts applied to a given college. This information is intended to help students focus their efforts on applying to the most suitable colleges, but it may also influence application decisions in undesirable ways. Using data on 70,000 college applicants across 220 public high schools, we assess the effects of access to Naviance on application undermatch, or applying only to schools for which a candidate is academically overqualified. By leveraging variation in the year that high schools adopted the tool, we estimate that Naviance increased application undermatching by more than 50% among 17,000 high-achieving students in our dataset. This phenomenon may be due to increased conservatism: Students may be less likely to apply to colleges when they know their academic qualifications fall below the average of admitted students from their high school. These results illustrate how information on college competitiveness, when not appropriately presented and contextualized, can lead to unintended consequences.

behavioral economics | higher education | recommender systems

Each year, more than one million US high school students apply to 4-y colleges (1). Completing college applications is both time-consuming and expensive, and the process yields uncertain outcomes. These factors make consequential decisions about where to apply particularly difficult and sometimes haphazard (2–6). Under the best circumstances, high school counselors can assist students as they navigate this high-stakes task (7). However, counselors themselves may have limited time, as they are often expected to manage average caseloads of hundreds of students (8, 9). Given this workload, counselors may struggle to provide students with accurate, personalized college recommendations. To fill this gap, high schools nationwide are increasingly turning to automated tools to help guide students in college search and application decisions (10).

One popular tool, called Naviance, shows students how recent graduates from their high school fared in prior application cycles and can help students quickly get a lay of the college admissions landscape. Its creators report that more than 40% of US high school students have access to Naviance through their high schools (11). The platform's signature data visualization is its scattergram, and, in Fig. 1, we show a stylized example scattergram for a fictional college. Each point in the plot indicates the grade-point average (GPA) and standardized test score (SAT or ACT) of a recent applicant to the college from the student's own high school, with acceptances indicated in green and rejections in red. The dashed lines indicate the average GPA and test scores for admitted applicants from the student's high school. To help ensure anonymity, a scattergram for a particular college is shown to a student only if the number of applicants to that college from the student's high school exceeds a minimum threshold. In this way, the choice set of colleges that students see in Naviance depends on the application behavior of prior cohorts from their same high school.

In recent work relying on data from one school district, Mulhern (11) showed that students indeed changed their application behavior in response to seeing Naviance scattergrams. In particular, Mulhern found that Naviance increased 4-y college attendance, especially among lower-income students, ostensibly because these students gained information about their college admissibility that they otherwise would not have received from other sources. Mulhern further found that Naviance deterred applications to selective colleges, for which the presented information indicated low likelihood of acceptance. In some cases, it may make sense for students to forgo sending applications to the most selective colleges, saving them the energy and expense of applying to schools

Significance

In an increasingly competitive academic environment, high school students often turn to data to inform their college application decisions. One popular tool to view historical admissions data, Naviance—used by hundreds of thousands of high school students each year—displays admissions outcomes for past applicants from a student's high school, highlighting the average grade-point average and standardized test scores of admitted students. We show that the adoption of Naviance inadvertently dissuaded many high-achieving high school students from applying to colleges for which they were competitive, increasing undermatching by 50% among this group of students. A more nuanced presentation of college admissions criteria could reduce this unintended consequence and improve educational outcomes.

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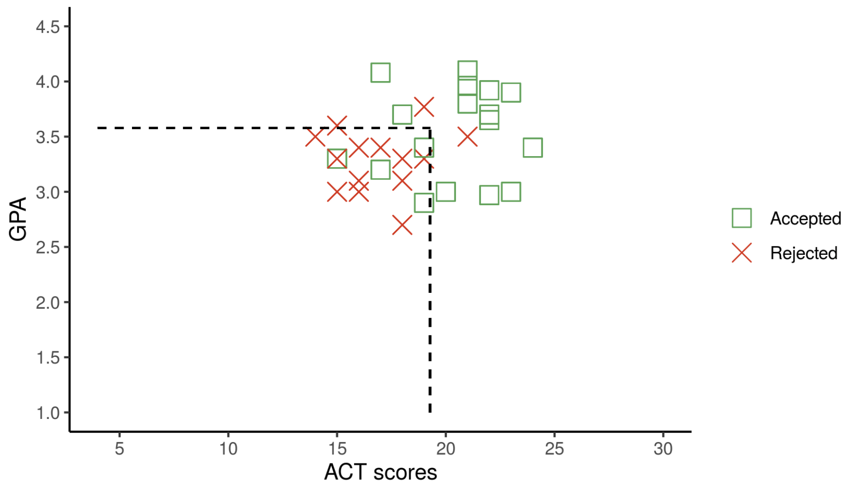

Fig. 1. An example scattergram for a hypothetical college, modeled after an open-source example from Wikimedia Commons. The points correspond to past applicants to the hypothetical college from a student's high school, with accepted applicants in green and rejected applicants in red. The dashed lines indicate the average GPA and test score among admitted applicants from the student's high school.

where they have little chance of acceptance. A concern, however, is that seeing past admissions outcomes could unreasonably discourage students from applying to selective colleges where they would, in fact, be competitive.

Here, in a large-scale empirical analysis—spanning approximately 70,000 students across 220 public high schools—we measure the effect of Naviance on potential application undermatching (12–15), where students apply only to schools for which they are academically overqualified. Undermatching has been shown to have several deleterious effects, impacting, for example, learning outcomes, college graduation rates, job satisfaction, and lifetime earnings (16). Especially for students from low-income backgrounds, failing to apply to highly selective schools for which they are competitive may be particularly detrimental (17–19). Not only do highly selective schools spend more per student on core educational activities and have higher graduation rates, but they also cost low-income students less to attend, owing to the generous need-based financial aid that these institutions provide (20–22). Finally, highly selective institutions can propel students from low-income families into high-income careers, advancing social mobility (23).

We find that adoption of Naviance caused application undermatching to increase by over 50% among the most academically competitive students—a group comprising a quarter of the students in our sample. This pattern persists even after adjusting for several potential differences in the pre- and post-adoption samples of students, including student test scores, GPA, race, gender, first-generation status, and use of an application fee waiver (a proxy for residing in a household with low income). We further find that among these high-achieving students, the increase in undermatching is most pronounced among those with the lowest test scores in this high-achieving group, a subset of students that may be more easily swayed by seeing the admissions outcomes of their peers.

Data and Methodology

To conduct our analysis, we filed public records requests to determine Naviance use with 50 large US school districts. We specifically aimed to identify those high schools that offer Naviance to their students, and for those that do, the application cycle in which they first made the tool available. Among the subset of schools that implemented Naviance in the period we consider, we combined school-level implementation information with detailed student-level information on where students submitted college applications using the Common Application. This rich set of data allows us then to compare application behavior before and after a school adopted Naviance.

Our public records requests allowed us to identify a diverse set of 220 US public high schools that used Naviance.[*] We then obtained anonymized, individual-level records documenting the colleges to which students attending these 220 high schools applied. Our college application data come from the Common Application—known informally as the Common App—a popular online platform for submitting college applications to nearly 1,000 4-y colleges and universities across the country. We ultimately analyzed data on 70,900 students who submitted 366,697 college applications through the Common App over five application cycles, from the 2014 to 2015 cycle to the 2019 to 2020 cycle.

To determine whether a student undermatched in their college application decisions, we first categorized the competitiveness of both colleges and students based on Barron's 2018 college ranking. Barron's arranges colleges into multiple tiers that reflect their selectivity. For example, a college that is classified as most competitive is one for which accepted students tend to have very high test scores and the school's acceptance rate is low. We collapse Barron's taxonomy into five categories, ranging from least to most competitive. We similarly determine a student's competitiveness based on their composite ACT or SAT score, with the thresholds chosen to mirror the average scores that Barron's reports for students accepted to schools in each corresponding category. Specifically, the ACT ranges for the five categories we consider are as follows: 1) under 21 for least competitive; 2) 21 to 23 for competitive; 3) 24 to 26 for very competitive; 4) 27 to 28 for highly competitive; and 5) 29 and above for most competitive. We say that a student undermatched if they exclusively applied to schools that are less competitive than their personal competitiveness rank.

[*]We began collecting data in the fall of 2019. This process was interrupted by the COVID-19 pandemic, as school districts halted operations in the spring of 2020, and we ultimately obtained responses from approximately half of the districts we contacted. Descriptive statistics characterizing these high schools is provided in *SI Appendix*.

Results

We start by estimating the effect of scattergrams on application undermatching by student competitiveness. To do so, we first split students into five groups based on their competitiveness. For each group of students, we then calculate the rate of undermatching in the first year that Naviance was available in their high school and compare it to the rate of undermatching in the year immediately preceding adoption of the tool.

We present the results of this initial, exploratory analysis in Fig. 2. We limit our exposition to the three most competitive groups of students, as students in our data who are less academically prepared rarely undermatch.[†] For the most competitive students—comprising 24% of students in our sample—we find that application undermatching rates increase by approximately 54% (95% CI: 39 to 69%) upon adoption of Naviance, from 15% undermatching in the year before Naviance was introduced into their high schools to 24% in the years when Naviance was available to them. For students who are less academically prepared, the estimated effects of Naviance on undermatching are considerably smaller and are not statistically significant. For these less academically prepared students, a larger share of colleges are at or above their match level, potentially making it easier to avoid undermatching and explaining the pattern we observe.

Fig. 3 expands on the results above by showing the year-to-year changes in application undermatching for the most competitive students, with the undermatching rate displayed for the 2 y before and after adoption of Naviance. To aid comparisons, the figure shows results for the 47 Florida high schools in our sample that adopted Naviance in 2016.[‡] We see pronounced jumps in undermatching after Naviance is introduced into the high schools, an effect that persists after the initial year of adoption.

Finally, we add quantitative detail to the visual summaries above by fitting logistic regression models to estimate the effect of adopting Naviance on undermatching, after accounting for other factors that may impact decisions about where to apply to college, and could potentially differ between our pre- and post-adoption samples of students. Our analysis strategy is akin to a within-school event study. We restrict our analysis to the subpopulation of most competitive students, as Fig. 2 suggests the effects are largely isolated to this group. In particular, we fit a logistic regression model of the following form:

$$\Pr(Y_i = 1) = \mathrm{logit}^{-1}(\alpha \mathbb{1}_{S(i)} + X_i\beta), \qquad [1]$$

where Y_i is a binary variable that indicates whether student i undermatched; $\mathbb{1}_{S(i)}$ indicates whether student i had access to Naviance scattergrams when applying to college (i.e., attended a high school during a year when Naviance was available there) and α its associated coefficient; and X_i is a vector of control variables with coefficient β. We fit three models with progressively more controls: 1) high school fixed effects; 2) high school fixed effects plus standardized test scores and cumulative GPA; and 3) high school fixed effects, test scores, GPA, student race, student gender, whether the student is the first in their family to attend college, and whether the student made use of Common App's fee waiver. These models complement our graphical pre/post analysis above by additionally adjusting for potential observable differences between students who did and who did not have access to Naviance when applying to college.

Table 1 displays the results of our regression analysis. Across all three model specifications, we find that adoption of Naviance substantially increased the likelihood that the most competitive students undermatch in their application decisions, consistent with the visual results shown in Figs. 2 and 3. We estimate that adoption of Naviance increased the odds of undermatching by 2.1 to 2.2 across models (i.e., $e^{\hat{\alpha}}$ is 2.1 under models 1 and 2 and is 2.2 under model 3; across models, the 95% CIs are contained in the interval 1.8 to 2.5). With approximately 15% of the most competitive students in our sample undermatching in their college applications prior to the adoption of Naviance, an estimated 2.1× increase in the odds of undermatching corresponds to a 27% estimated undermatching rate after adoption of Naviance, all else being equal.

The effects of Naviance on undermatching are substantial and point to potential missed educational opportunities for the most competitive students. To further quantify the effect of Naviance on the quality and selectivity of the schools to which students apply, we use three metrics common in the literature (24): 1) teaching expenditures per student; 2) 4-y graduation rate; and

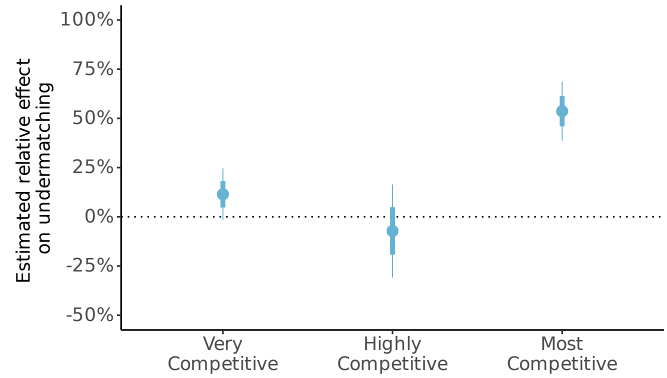

Fig. 2. Estimated effect of adopting Naviance on undermatching, disaggregated by student competitiveness. The effect of Naviance is concentrated among the most academically prepared students.

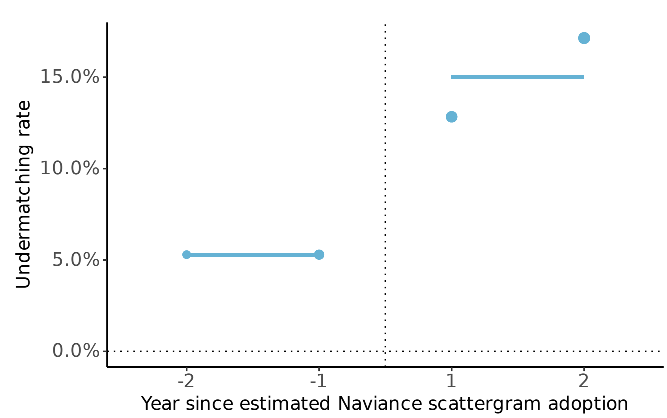

Fig. 3. Estimated effect of Naviance on undermatching for the most competitive students, with undermatching rate shown in the 2 y before and after adoption of Naviance, for the 47 Florida high schools that adopted Naviance in 2016.

[†]Our individual-level data are composed of students who applied to at least one college through the Common App. Among the least academically prepared students, most colleges are at or above their match level, and so, applying to any college is typically sufficient to avoid application undermatching.

[‡]This is the largest sample for which we can assume relatively stable and comparable conditions across all four years considered. In particular, we have the most data from the year 2016, when the majority of school districts purchased Naviance. Further, the state-specific college market is a large influence on where students apply, and by focusing on the state of Florida, we ensure that students have a reasonably similar college market across the 4 y displayed. Recent data indicate that nearly 80% of college-bound students from Florida remain in-state for college (https://floridacollegeaccess.org/news/what-percentage-of-students-leave-florida-to-go-to-college/).

Table 1. Estimated effects of Naviance on undermatching for the most academically competitive students

	Dependent variable:		
	Student undermatched		
	(1)	(2)	(3)
Access to Naviance	2.1***	2.1***	2.2***
(95% CI)	(1.8, 2.4)	(1.9, 2.4)	(2.0, 2.5)
	Maximum SAT score		
	(1)	(2)	(3)
Access to Naviance	−7.94***	−8.33***	−8.68***
(95% CI)	(−9.68, −6.20)	(−10.03, −6.63)	(−10.38, −6.99)
	Maximum graduation rate		
	(1)	(2)	(3)
Access to Naviance	−2.18***	−2.30***	−2.43***
(95% CI)	(−1.67, −2.69)	(−1.80, −2.80)	(−2.93, −1.93)
	Maximum student spending		
	(1)	(2)	(3)
Access to Naviance	−6,745***	−7,246***	−7,817***
(95% CI)	(−8,272, −5,218)	(−8,706, −5,786)	(−9,254, −6,379)
Controls			
Standardized test scores	—	Yes	Yes
Cumulative GPA	—	Yes	Yes
Race	—	—	Yes
Gender	—	—	Yes
First generation status	—	—	Yes
Used Common App fee waiver	—	—	Yes
High school fixed effects	Yes	Yes	Yes
Observations	17,243	17,243	17,243

The main effect is expressed on the odds scale (i.e., we show, in the *Top* row, the exponentiated coefficient from logistic regression models). Across various model specifications, we find that the adoption of Naviance increased undermatching. Overall, prior to the adoption of Naviance, 15% of the most competitive students undermatched. We additionally estimate the effect of Naviance on the quality of the basket of colleges to which students apply, as summarized by the maximum SAT score, graduation rate, and per-student spending among a student's selected colleges. For these quality metrics, we estimate effects with linear regression. In all three cases, we find statistically significant and substantively meaningful reduction in quality caused by the adoption of Naviance. Note: $^{*}P < 0.1$; $^{**}P < 0.05$; $^{***}P < 0.01$.

3) 75th percentile of SAT math scores for the incoming class. For all three of these school quality measures, we first compute, for each student i in our sample, the largest value Q_i of that measure among the schools to which the student applied. For example, in the case of graduation rates, if a student applied to four colleges, with graduation rates equal to 50%, 60%, 80%, and 90%, respectively, we would set Q_i to 90%. We then fit three separate linear regression models—one for each of the three metrics—to estimate the effect of adopting Naviance on each measure of quality. Specifically, we fit models of the form:

$$Q_i = \alpha \mathbb{1}_{S(i)} + X_i\beta + \epsilon_i, \qquad [2]$$

where Q corresponds to a measure of school quality, and the remaining terms are analogous to those in Eq. **1** (i.e., $\mathbb{1}_{S(i)}$ indicates whether the student had access to Naviance, and X_i are control variables).

As shown in Table 1, we find that access to Naviance leads to a significant reduction in the quality of schools to which the most competitive students apply. Specifically, all else being equal, we find that adoption of Naviance leads students to apply to colleges with approximately $7,000 less per-student spending, approximately 9 points lower math SAT scores, and approximately 2 percentage points lower graduation rates.

Our results show that Naviance increased undermatching among high-achieving students, with meaningful drops in the overall quality of colleges these students applied to. To further illustrate the impact of Naviance on college application decisions, we next consider the specific institutions to which high-achieving students applied before and after adoption of Naviance. As before, to facilitate interpretation, we consider the subset of students who attended high schools in Florida. Fig. 4 shows changes in the relative popularity of colleges among applicants before and after adoption of Naviance, for the subset of colleges that were among the 10 most popular choices either before or after Naviance was adopted. For example, among high-achieving students, one particular institution rated as most competitive received the third-most applications prior to the adoption of Naviance, but dropped out of the top ten after Naviance was introduced. Conversely, after Naviance was introduced, high-achieving students were much more likely to apply to local colleges, all of which were relatively unpopular choices prior to the adoption of Naviance.

We can only speculate about why Naviance caused a shift to these particular colleges. We note, though, that with Naviance, students can see the approximate number of applications submitted to each college by students in previous cohorts at their high school. It is thus possible that adoption of the tool caused high-achieving students to focus on options generally popular among

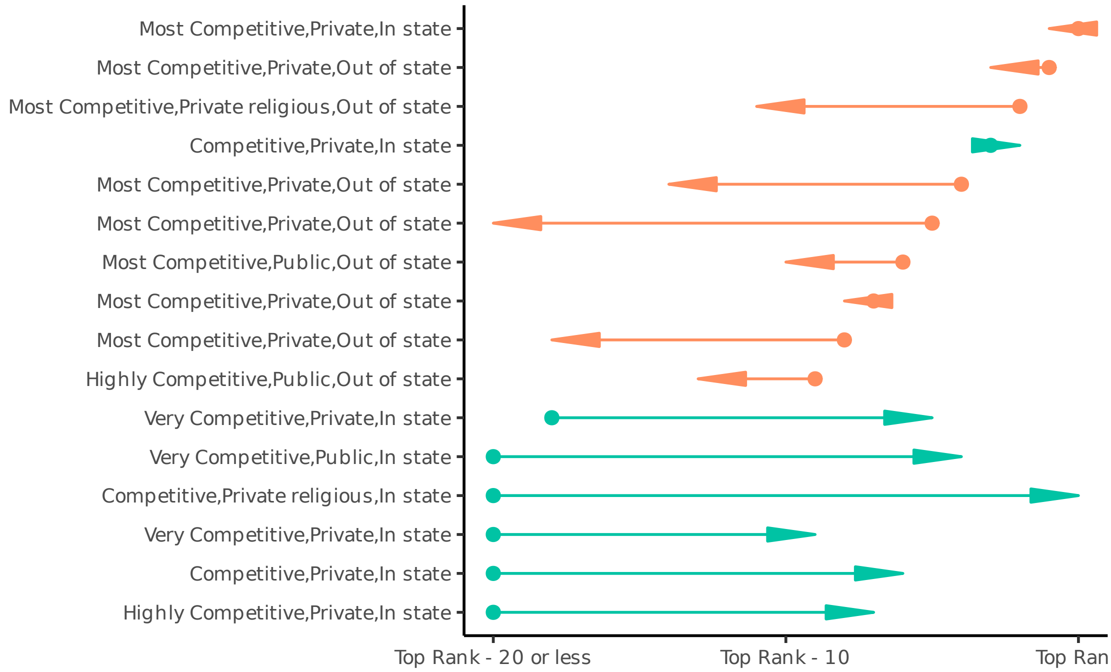

Fig. 4. Changes in the relative popularity of colleges among high-achieving applicants who attended high schools in Florida. We include all colleges that were among the 10 most popular (i.e., received the most applications) either before or after Naviance was adopted, with colleges displayed along the vertical axis in order of their popularity prior to the adoption of Naviance. For each college, the arrow points from its pre-Naviance rank to its post-Naviance rank, with green arrows corresponding to increases in popularity and orange arrows corresponding to decreases. After adoption of Naviance, high-achieving students were more likely to apply to less competitive colleges located in Florida rather than to the most selective national colleges that were popular choices prior to Naviance, contributing to undermatching. To respect each institution's anonymity, instead of their name, we display their Barron's selectivity ranking, whether they are public or private, and whether or not they are in Florida.

their peers, which in many cases are less competitive, in-state institutions.

We have so far considered the aggregate impact of Naviance on high-achieving students as a whole. We conclude our analysis by examining heterogeneity among this subpopulation. In Fig. 5, we see that among the most competitive students, it is those with the lowest relative test scores who are most impacted by Naviance. Prior to the adoption of Naviance, the rate of undermatching was largely similar across students stratified by test scores—although those students at the very lowest end of the high-achieving range, with an ACT score of 29, did undermatch at relatively higher rates. However, after the adoption of Naviance, the gap in undermatching between the most- and least-competitive of the high-achieving students became much more pronounced.

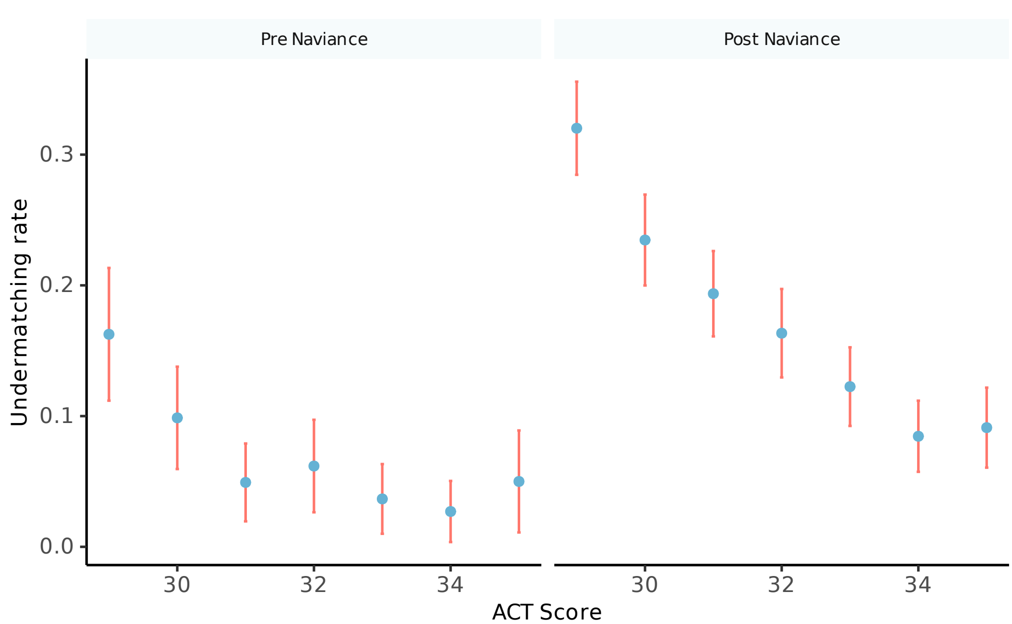

Fig. 5. The rate of application undermatching among high-achieving students as a function of test score, before and after adoption of Naviance. To facilitate comparisons, we restrict to the set of applicants who attended a high school in Florida. The effect of Naviance on undermatching appears to be largest among students with the lowest test scores among this high-achieving group.

Consider, for example, students with an ACT score of 31, which would place them among the top 5% of test takers. Prior to Naviance, these students undermatched at rates similar to those with an ACT score of 35, in the top 1% of test takers. But after adoption of Naviance, the undermatching rate of students with a test score of 31 was nearly twice as high as those with a test score of 35.

We corroborate the visual pattern in Fig. 5 by fitting a model of undermatching analogous to that in Eq. **1**, but with the additional interaction term $\mathbb{1}_{S(i)} \times T_i$, where $\mathbb{1}_{S(i)}$ indicates whether student i had access to Naviance and T_i is their ACT score. This augmented logistic regression model is then fit across our full dataset of high-achieving students. We find that the coefficient on the interaction term is −0.067 (SE: 0.028; P value: 0.017), showing that high-achieving students with higher test scores are less likely to undermatch—or, equivalently, that those with relatively lower test scores are more likely to undermatch, consistent with the trend in Fig. 5.

It is difficult to definitively determine the mechanism behind this pattern. But one possibility is that students on the lower end of the high-achieving range might see, through using Naviance, their test scores fall below the average of their admitted peers at some of the most competitive colleges. These slightly less competitive students might accordingly be dissuaded from applying to the most selective colleges. In reality, though, these students would still be good candidates for admission at many of the most competitive colleges, and so not applying to them could lead to undermatching. Indeed, whether a student falls above or below the average of past students admitted from their high school is a noisy proxy for a college's admissions standards.

Discussion

In a large-scale analysis of college application decisions—comprising 70,000 students at more than 200 high schools across the United States—we found that showing high-achieving students the past admissions outcomes of their peers increased application undermatching by more than 50%. In particular, it appears that the adoption of Naviance disproportionately increased undermatching among students on the lower end of the high-achieving range, with these students dissuaded from applying to selective colleges where they would still be competitive. Such application undermatching can have serious consequences, including deleterious effects on graduation rates, educational performance outcomes, job satisfaction, and lifetime earnings.

We note, though, that Naviance likely has positive impacts on some students. For example, Mulhern (11) found evidence that Naviance nudged some students—particularly Black, Hispanic, and lower-income students—to enroll in 4-y colleges who otherwise would have enrolled in community colleges. In our own analysis, we found that Naviance increased the number of colleges students applied to by, on average, one application per student (*SI Appendix*, Tables S1 and S2).

One limitation of our analysis is that we only consider application undermatching as opposed to enrollment undermatching since we do not have access to the enrollment decisions of students. If students undermatch in their application decisions, then they necessarily undermatch in their enrollment decisions, but, it is possible in theory that the causal effects of Naviance on enrollment undermatching are attenuated. Similarly, given the scope of our data, we are unable to examine longer-term outcomes, like college graduation and employment. Further, our conclusions ultimately are based on a non-representative sample of public US high schools that responded to our requests for data, which may exhibit trends that differ from those in the population as a whole. Nonetheless, we believe that our findings point to an important phenomenon, and we hope that future work can address the limitations of our study.

It is difficult to identify the precise mechanism through which Naviance increased application undermatching, but it is likely due in part to its specific visual display of past admissions outcomes (11). By highlighting the average GPA and test scores of previously admitted students, Naviance might encourage students or their mentors—including high school counselors and parents—to overly anchor to those metrics, masking the fact that approximately half of admitted students necessarily have below-average academic credentials.

It is possible that simple changes to the visual display of information could mitigate the negative impacts of Naviance on high-achieving students. For instance, one could highlight regions of competitiveness, rather than just indicating the averages, to limit an inappropriate focus on the latter. Further, the set of displayed colleges are often limited to those that previously received a minimum number of applications from a student's high school, which could similarly encourage high-achieving students to simply follow the application decisions of their peers, even if they would be competitive at more selective colleges. To address this concern, high-school-specific information might be combined with regional or national statistics to ensure users see a range of options. Last, the interface could be redesigned to emphasize the portfolio of colleges students might apply to, rather than focusing on individual colleges in isolation. Such a change could encourage students to apply to an appropriate mix of "safety," "match," and "reach" schools. We stress, though, that any changes to the Naviance interface should be thoroughly tested and audited to guard against unintended consequences, drawing on existing work on how people process data-driven visualizations (25).

Finally, we connect our work to the burgeoning literature on the equitable design of algorithms (26–28). Predictive algorithms are now routinely used to guide high-stakes decisions in medicine, banking, criminal justice, and beyond (29–33). To help ensure that these tools do not exacerbate inequities, a plethora of formal methods have emerged to quantify their "fairness" (34–39). But comparatively little attention has been paid to the behavioral responses to such algorithms (40, 41). Our findings illustrate that even when accurate information is presented to students, it may still lead to problematic outcomes. Looking ahead, we hope future research continues to investigate the subtle ways in which humans and algorithms interact in order to design tools that help us achieve broadly equitable ends.

Materials and Methods

In the study period, most highly ranked universities in the United States required that applicants send official score reports for one of two standardized tests, the ACT or the SAT. While not mandatory, applicants can unofficially report their GPA and standardized test scores via the Common App. Our analysis includes only those applicants who chose to unofficially report their SAT or ACT score via the Common App. Applicants have little incentive to misrepresent their GPA or test scores on the Common App, as the reported values can be verified by the university using official score reports and official transcripts. For ease of interpretation, we convert all standardized test scores to the ACT scale. We use the official, publicly available conversion tables provided by the administrators of the ACT to convert from the 400 to 1,600 SAT scale to the 1 to 36 ACT scale.[§]

[§] https://www.act.org/content/dam/act/unsecured/documents/pdfs/ACT-SAT-Concordance.pdf.

We use the single highest score among each applicant's reported ACT score and ACT-equivalent SAT score.

To estimate effects of undermatching on the long-term outcomes of teaching expenditures per student, 4-y graduation rate, and 75th percentile of SAT math scores for the incoming class, we use the Integrated Postsecondary Education Data System (42). This dataset makes available several measurements with which we constructed the derived quantities above following Goodman et al. (24).

We have released de-identified, aggregate-level data sufficient to qualitatively replicate our main results, including undermatching rates by high school and year. To preserve privacy, we are not releasing individual, student-level data.

Data, Materials, and Software Availability. Analysis code and data to qualitatively replicate the main analysis have been deposited in Github (https://github.com/politechlab/replication_nav) (43). For privacy reasons we cannot release further data. However, we will release aggregate-level data sufficient to qualitatively replicate our main results.

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