Cameras of Merit or Engines of Inequality? College Ranking Systems and the Enrollment of Disadvantaged Students[1]

James Chu
Columbia University

The expansion of ranking systems has increased public access to information about organizations, but there is burgeoning concern that rankings reduce the accessibility of goods and services for individuals from lower socioeconomic status backgrounds. The evidence and underlying theory for this claim, however, remain unclear. This article develops two possibilities: (1) positional advantage, where rankings increase demand for better-ranked organizations and crowd out disadvantaged individuals; and (2) algorithmic trade-offs, where rankings lead organizations to optimize on criteria that are in tension with serving individuals from disadvantaged backgrounds. Scope conditions for these theories are established, and key predictions are tested with administrative data matched with *U.S. News & World Report* college rankings between 1997 and 2015. This research clarifies how the consequences of ranking systems spill over from organizations to broader social inequalities and demonstrates when and how rankings contribute to structural barriers to upward mobility.

Over the past 30 years, ranking systems have proliferated across nearly all organizational domains (Fombrun 2007; Hazelkorn 2015; Snyder and Cooley 2015). These rankings publicly quantify and codify the overall value of organizations, helping individuals identify the "best" colleges, restaurants, firms, and hospitals. The rapid expansion of such systems, however, has also animated

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concern about whether ranking systems truly act as "cameras" that neutrally reflect the merit of organizations or whether they also act as "engines" that actively reshape and reconfigure society (Hollis and Lukes 1982; Hacking 1990; Porter 1995; Strathern 2000; MacKenzie 2008). Research shows that prominent rankings not only reflect but also influence public perceptions about what is valuable (Espeland and Stevens 1998; Fourcade 2011; Lamont 2012; Correll et al. 2017; Esposito and Stark 2019). For instance, hospitals and schools that move up in their rankings receive more patients and applicants, even when the underlying characteristics of these organizations are held constant (Monks and Ehrenberg 1999; Meredith 2004; Sauder and Lancaster 2006; Griffith and Rask 2007; Dranove and Sfekas 2008).

Although existing theories and empirical findings establish that ranking systems affect how organizations are perceived, this only takes us halfway toward claims that rankings have widespread social consequences. Prior work has focused on the effects of rankings on organizations themselves, but organizations are socially embedded with diverse stakeholders, and it is important also to understand how ranking systems affect the social impact of organizations. In particular, commentators have cast rankings as an exemplar of "weapons of math destruction," which have "great scale, inflict widespread damage, and generate an almost endless spiral of destructive feedback loops" (O'Neil 2016, p. 51). Although organizational rankings are designed to help individuals find jobs, meals, educational opportunities, or health care, a prominent criticism is that they also restrict the accessibility of these important goods for people from lower socioeconomic status backgrounds (e.g., Tepper 2017; Wermund 2017). If true, the expansion of rankings could contribute to the income inequalities and stalled patterns of social mobility observed in recent studies (Chetty et al. 2014; Piketty 2014). But what is the theory behind this criticism? When and how does the introduction of a ranking system exacerbate inequalities between socioeconomic groups, and what is the evidence to support these claims?

This article develops and tests two theoretical explanations. First, when organizations are exposed to widely perceived rankings, resources and attention tend to shift from lower-ranked to higher-ranked organizations. This dynamic of *positional advantage* increases inequalities among organizations, and positional advantage may also translate into differences in whom the organizations serve. To the extent that rankings increase demand for goods and services of higher-ranked organizations, and capacity to meet this demand is

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limited, higher-ranked organizations may become more selective in whom they serve (e.g., by charging higher prices). This increase in selectivity favors individuals with more resources and thereby displaces individuals from lower socioeconomic status backgrounds.

A second possibility is motivated by research on “reactivity,” which emphasizes that organizations change their activities in response to being evaluated (Luca and Smith 2015; Askin and Bothner 2016; Espeland and Sauder 2016; Kim 2018). This line of research offers an “orienting heuristic” (Espeland and Sauder 2007, p. 33), and I draw on this framework to propose a dynamic of *algorithmic trade-offs*, whereby exposure to rankings leads organizations to reallocate resources to optimize on ranking criteria and, because resources are zero sum, trade off focus on other important outcomes. In situations where the criteria of a widely perceived ranking system fail to value the accessibility of goods and services for consumers from all socioeconomic backgrounds, organizational attempts to maximize on their rankings will divert efforts away from ensuring this outcome.

Evaluating these possibilities is empirically challenging, and prior research has yet to conclusively test these possibilities. The primary challenge is that ranking systems are designed to formally represent the characteristics of organizations. This fact complicates efforts to isolate the effects attributable to rankings from the characteristics that they represent. For instance, tests for positional advantage must identify whether improvements in rankings, independent of all other characteristics, lead to downstream changes in whom an organization serves. Such exogenous changes in rank are, however, rare. Similarly, a test for algorithmic trade-offs should compare organizational outcomes when they are ranked versus not ranked. Interview data suggest that the introduction of rankings encourages organizational leaders to optimize on rankings (Stevens 2007; Espeland and Sauder 2016), but existing evidence does not tell us whether organizational leaders would have optimized on the same outcomes prior to being ranked. It is even possible that the imposition of rankings increases the clarity of where organizations fall in a status system and reduces the degree to which organizational actors feel compelled to optimize on their rankings (Gould 2003; Halevy, Chou, and Galinsky 2011).

This article addresses these empirical challenges through an examination of the *U.S. News & World Report* (*USNWR*) college ranking system and its effects on the distribution of higher education opportunities between 1997 and 2015. Higher education opportunities constitute one of the most valuable resources in modern society (Card 1999; Brand and Xie 2010; Torche 2011; Hout 2012). To what extent can a ranking system, produced by a magazine with no regulatory authority, affect the accessibility of higher education opportunities for students from lower socioeconomic status backgrounds (hereafter, “disadvantaged backgrounds”)? To disentangle the consequences attributable to ranking systems from social processes that would exist in their absence, I draw on three quasi-experimental strategies: difference in difference, regression discontinuity, and matching.

The results support a theory of algorithmic trade-offs. Exposure to *USNWR* rankings led colleges to reduce the share of disadvantaged students, either defined as Pell grant recipients or first-generation students, enrolled between 1997 and 2015. Mediation analyses further suggest that these results are driven by attempts to maximize on criteria like test scores. Moreover, results from this study contradict a theory of positional advantage as a driver of inequality. Results show that better-ranked colleges would have enrolled the same proportion of disadvantaged students in a counterfactual world where they were not ranked. Surprisingly, exposure to rankings led *lower*-ranked colleges to reduce their enrollment of disadvantaged students. I conjecture that organizations that enter in lower-ranked positions must take more action to avoid falling further behind than organizations in advantaged positions must take to maintain their positions. Moreover, as rankings lead more resources and attention to flow to higher-ranked organizations, lower-ranked organizations have fewer resources and thus face larger trade-offs when optimizing on the rankings. This ultimately leads them to enroll fewer disadvantaged students as a downstream consequence.

THEORETICAL FRAMEWORK

Since the meteoric expansion of ranking systems in the late 20th century, there has been ongoing interest in the social consequences of rankings. Researchers have observed that rankings have the capacity not only to represent but also to change what people perceive as valuable, such that inaccuracies within a ranking system become self-fulfilling (Espeland and Stevens 1998; Salganik and Watts 2008). Recent scholarship has begun to examine the spillover effects of ranking systems and other quantitative devices beyond the boundaries of what they formally evaluate (boyd and Crawford 2012; Brayne 2017; Eubanks 2018; O'Brien and Kiviat 2018). I extend this line of research here by articulating two theoretical possibilities for how and when ranking systems reduce the accessibility of goods and services for individuals from disadvantaged backgrounds. These possibilities are compatible and may even complement one another. As we will see, however, they are distinctive in their theoretical and policy implications.

Positional Advantage

The first possibility is based on a dynamic of *positional advantage*: better-ranked organizations are more visible, tend to receive more resources, and attract more demand for their goods and services. Pope shows that hospitals experience up to a 5% increase in patient volume as a result of improvements in their rank (2009). Leveraging a natural experiment, Luca and Smith find that a one rank improvement in college rankings increases the number of applications to a college by one percentage point (2013). Bastedo and Bowman use structural equation modeling to show that peer colleges gave poorer assessments to colleges that fell in their college rankings, even when these declines were uncorrelated with characteristics of the college (2009). More generally, individuals act on social cues about what is valuable and prefer better-ranked over lower-ranked options (Salganik, Dodds, and Watts 2006). These dynamics may be especially pronounced in domains where the value of an option is contingent on how much others value it, such that individuals use rankings as a coordination device to identify what other people believe is valuable (Karpik 2010; Chwe 2013; Correll et al. 2017, p. 299; Esposito and Stark 2019).

Positional advantage implies that organizations experience increasing inequalities in the distribution of demand for their goods and services. Building on this insight, I propose that positional advantage may also have downstream ramifications for whom the organization serves. If capacity to meet demand is relatively fixed, as when restaurants cannot rapidly add additional seating or colleges cannot expand enrollments, then organizations receiving greater demand must adopt sorting mechanisms to determine who receives their limited services. A canonical economic solution to this problem is to raise prices, which screens for consumers that are willing and able to pay more. In cases where organizations have existing screening processes, as in the case of employee hiring or college admissions, an alternative solution is to increase the standards for admission. For instance, a highly ranked firm that receives more job applications could further screen for employees that they deem desirable (e.g., Rivera 2015). On average, individuals from higher socioeconomic status backgrounds are better equipped to pay higher prices or pass the screening of these organizations. As such, increasing demand for higher-ranked organizations leads such organizations to serve individuals from more advantaged backgrounds and crowd out those from disadvantaged backgrounds.

In principle, it is possible that the expansion of rankings selectively increases demand for higher-ranked organizations among individuals from disadvantaged backgrounds (Peterson et al. 1998; Marshall et al. 2000). For instance, Hoxby and Turner (2015) find that low-income students fail to apply for beneficial college opportunities because they lack information about these opportunities. More generally, sociologists have long pointed to a desire for "equality under the law" as a driver of rationality and quantification (Weber [1922] 1978, pp. 979–80). Drawing on these ideas, publishers of rankings claim that their products reduce information gaps between everyday people and individuals that can afford access to privileged information (e.g., private college counseling; Hannan et al. 1994; Morse 2017). One problem with this logic, however, is that individuals from privileged backgrounds are better equipped to capitalize on information about which organizations are better or worse (Hasan and Kumar 2019). Indeed, research shows that ranking signals are more likely to change the choices of individuals from higher socioeconomic backgrounds, perhaps because they are better equipped to access opportunities they desire (McDonough et al. 1998; Higher Education Research Institute 2007).

Taking these ideas together, positional advantage predicts that organizations assigned to higher-ranked positions will receive more demand for their goods and services than those in lower-ranked positions. If organization capacity is relatively fixed, higher-ranked organizations will become more selective in whom they serve, often in ways that exclude individuals from lower socioeconomic backgrounds. By contrast, lower-ranked organizations will be less selective in whom they serve. Note that a theory of positional advantage does not predict overall changes in the accessibility of organizations for disadvantaged individuals. This is because any reduction in accessibility for disadvantaged individuals is counterbalanced by an increase among lower-ranked colleges. Instead, positional advantage predicts greater sorting, where advantaged individuals are more likely to be served by higher-ranked organizations and disadvantaged individuals by lower-ranked organizations.

Algorithmic Trade-Offs

To develop a second possibility that can explain overall changes in the accessibility of organizations, I posit a dynamic of *algorithmic trade-offs*, whereby organizations reallocate their resources to optimize on the criteria featured in the rankings at the expense of other important outcomes. Notably, public ranking systems have no authority to threaten or compel organizations to change their behavior. This differs markedly from restaurant hygiene or state-mandated hospital accountability systems, which may use rankings to compel organizations to improve specific outcomes (e.g., Dranove et al. 2003; Jin and Leslie 2003; Sharkey and Bromley 2015). However, as research on reactivity shows, ranking systems change organizational behavior by offering clear metrics that organizations can manipulate and improve (Espeland and Sauder 2007, p. 25). Exposure to widely perceived rankings leads to a narrowing of competition along the outcomes specified by the ranking algorithm. The distillation of status into a set of discrete, achievable measures leads to increased focus on these dimensions at the expense of others. This dynamic is also why evaluative systems lead to increasing focus on citations for academics and "counting clicks" among journalists (Christin 2018; Biagioli and Lippman 2020).

As organizations reallocate resources to optimize on a narrow set of outcomes, the zero-sum nature of resources requires trade-offs on other outcomes. This is a form of what Merton called the "imperious immediacy of interest," where "an actor's paramount concern with the foreseen immediate consequences excludes the consideration of further or other consequences" (Merton 1936, p. 901). Rankings present immediate and quantifiable consequences to organizational actors, who are unable to maximize on all outcomes, even other outcomes they value, because they are limited by zero-sum resources and attention. Money or time spent pursuing one outcome comes at the expense of another. Although optimizing on a ranking algorithm is "behavior that is rational within a situational context, . . . organizations produce unanticipated negative consequences that deviate from formal design goals and normative standards" (Vaughan 1999, p. 298).

When might this dynamic lead organizations to reduce the accessibility of their goods and services for individuals from disadvantaged backgrounds? In situations where the criteria of a widely perceived ranking system fail to value the accessibility of goods and services for consumers from all socioeconomic backgrounds, organizational attempts to optimize on such a ranking will result in the diversion of efforts from ensuring accessibility to the maximization of other ranking criteria. This diversion, in turn, reduces the accessibility of organizations for individuals from disadvantaged backgrounds—even more than would occur in the absence of rankings. I call this theory *algorithmic trade-offs* because it predicts that rankings exacerbate patterns of socioeconomic inequality as a consequence of active efforts among organizations to optimize a ranking algorithm that does not positively value accessibility, rather than as the passive result of positional advantage.

Although a dynamic of algorithmic trade-offs may be intuitive, this is not evidence of its explanatory power but rather warrants additional theoretical development and empirical examination. In particular, the scope of this theory is significantly more limited than a theory of positional advantage. Two conditions are necessary for the general dynamic of algorithmic trade-offs to occur: (1) the theory only applies when organizations can manipulate their ranked outcomes and (2) the criteria of the ranking system must be known to organizations. Two additional conditions link this dynamic to accessibility for disadvantaged individuals: (1) organizations must have some existing commitment to ensuring accessibility (or there is nothing to trade off) and (2) widely perceived ranking systems fail to value accessibility. When are these conditions likely to be met? In some organizational fields, the prestige of an organization's clientele increases the prestige of the organization. Examples where this dynamic occurs include colleges, nightclubs, investment banks, and consulting firms (Bastedo and Bowman 2009; Podolny 2010; Mears 2020). I conjecture that, in such fields, rankings will fail to positively value the inclusion of individuals from lower socioeconomic backgrounds.

This is because a ranking system that tries to embody alternative logics would likely be displaced by a ranking system that better captures preexisting status intuitions, in the same way that rankings like *USNWR* have thus far easily fended off challenges by ranking systems that prioritize alternative criteria. After all, "any group could arbitrarily announce a competition to anyone, for almost anything; but most people would reject a wide range of such possibilities as socially inappropriate or absurd" (Goode 1978, p. 163).

Moreover, ranking systems are one external pressure in a legion of potentially competing pressures that organizations face. Organizations routinely react to public demands or reputational pressures through ceremonial changes (e.g., decoupling), but research suggests that organizations are less able to decouple from the demands of rankings (Sauder and Espeland 2009, p. 64). One reason that rankings are more powerful than generalized public pressure is that they offer concrete levers that an organization can optimize to improve its standing, whereas other pressures are less enforceable and actionable. Of course, some competing pressures become institutionalized in policies with concrete measures and metrics, such that they counterbalance organizational attempts to optimize on rankings. For instance, the rise of affirmative action policies and public awareness around racial discrimination have generated specific pressures to increase the proportion of racial minorities that organizations serve (Espenshade and Chung 2005; Espenshade and Radford 2009; Dobbin, Kim, and Kalev 2011; Dobbin, Schrage, and Kalev 2015; Warikoo 2016). This suggests that organizations with clear affirmative action policies are resistant to algorithmic trade-offs, even when the ranking system fails to value accessibility for racial minorities. By contrast, external pressures to ensure equal accessibility across socioeconomic backgrounds have been less salient than those around racial representation, even as there is growing interest in class-based affirmative action policies and the inclusion of socioeconomic diversity as a metric in the rankings (e.g., Reardon et al. 2018). As these policies become more widespread, they may also limit the extent to which algorithmic trade-offs restrict accessibility.

THE CASE OF *USNWR* COLLEGE RANKINGS

To test these implications, I draw on the case of contemporary higher education in the United States and the *USNWR* college rankings. The *USNWR* is the best-known ranking system for colleges in the United States. Although there are multiple college rankings, *USNWR* remains the most widely used and prominent brand of college rankings (Clarke 2002). Each August, it publishes its college rankings issue. If one measures the popularity of rankings by the number of website visitors who access the rankings, the *USNWR* web site receives 10 million views after it publishes college rankings, while the website typically only receives 500,000 daily visitors (Freedman 2007). Its popularity has also made it a target of criticism. Journalists have documented how colleges respond to the *USNWR* rankings by reporting false data or asking students to retake standardized examinations (Farrell and Van Der Werf 2007; de Vise 2011; Kutner 2014). Although these examples illustrate how colleges subvert the intentions of ranking agencies, these articles neither claim nor empirically establish that these actions limit access for disadvantaged students in the aggregate. This is what the current article examines.

The case fits the scope conditions of both theories: it is a widely perceived ranking system that publicly quantifies the overall value of organizations. Its criteria and weights are visible to organizations. Higher education institutions generally are unable to rapidly scale up the provision of spaces, and their ability to rapidly meet demand is constrained. Moreover, the criteria used in the rankings do not positively value accessibility and may even be in tension with this goal. In particular, from 1996 to 2015, the *USNWR* rankings were based on 16 quality indicators, which were aggregated into seven weighted categories and used to create a final ranking. While there have been minor changes to the weights over time (Clarke 2002), the seven categories are as follows: academic reputation (25%), faculty resources (20%), average graduation and retention rate (20%), student selectivity (15%),[2] financial resources (10%), alumni giving (5%), and graduation rate relative to the previous year (5%). Colleges that optimize on their rankings may trade off efforts to ensure accessibility for low-income or first-generation students, who tend to perform worse, on average, on several of these indicators: first-generation students score lower on college admissions examinations than students who have at least one parent who graduated from college (Balemian and Feng 2013); first-generation students are 1.25 times more likely to leave their institutions than students who have at least one parent with any college education (Ishitani 2006, p. 871); and retention rates among low-income and first-generation students are substantially lower than among more advantaged students (Thayer 2000).

The case is also of substantive and theoretical importance for sociologists of education. Despite the rapid expansion of higher education opportunities, stratification in higher education has persisted over the past century (e.g., Raftery and Hout 1993; Shavit and Blossfeld 1993; cf. Arum, Gamoran, and Shavit 2007). Individuals from lower-class backgrounds, such as those from lower-income households with primary guardians who never graduated from college, remain less likely to enroll in college than their advantaged peers

[2] The proportion of students graduating at the top 10% of their high schools and average SAT scores are indicators under student selectivity, which comprise the student selectivity category (Clarke 2002).

(Ellwood and Kane 2000; Lucas 2001; Breen and Jonsson 2005; Alon 2009). In the United States, the National Center for Education Statistics estimates a 30-percentage-point gap in college attendance between high- (top 20th percentile) and low- (bottom 20th percentile) income households (Ross et al. 2012).[3]

Prevailing explanations for this gap in college attendance highlight the role of colleges as gatekeepers that select for individuals from higher socioeconomic status backgrounds (Tilly 1998; Bastedo and Jaquette 2011; Posselt 2016; Bowen and Bok 2016; Domina, Penner, and Penner 2017). The fact that colleges prefer individuals with higher-status backgrounds is generally taken for granted, leading scholars of educational inequality to focus on obstacles at the student and household level (e.g., Massey et al. 2003, p. 5). For instance, students from low-income backgrounds may be unable to access sufficient liquidity or financial aid to pay for college and its related opportunity costs (Ellwood and Kane 2000; Goldrick-Rab 2016). The environments they grow up in may foster cultural traits that are not rewarded by school systems (Carter 2005; Lareau 2011). They are exposed to different expectations and lower-quality educational opportunities from an early age, leveling both their aspirations and achievement levels (Bowles and Gintis 1976; McLeod 2008; Reardon 2011). Moreover, students may lack knowledge about existing financial aid resources or college opportunities (Hoxby 2007; Bettinger et al. 2012).

The theories developed here reverse these traditional emphases. Rather than taking the gatekeeping functions of colleges for granted and focusing on deficiencies at the student or household level, the theory implies that how colleges sort students is a partial function of how colleges are ranked. Moreover, higher education institutions must respond to competition and pressures from their environment (e.g., Kirst and Stevens 2015). Students and families frequently package and market themselves to attain positions in prestigious institutions. Yet the pressures that colleges face are equal to or perhaps even greater than those faced by students (Grodsky 2007; Colyvas 2012). As colleges evaluate and sort students, colleges are also seeking to optimize their standing in ranking systems that evaluate and sort them. If the theories proposed in this article are supported, ranking systems may partially explain why colleges so frequently sort students in ways that perpetuate unequal distributions of higher education opportunities.

[3] Stratification is also occurring horizontally, with colleges of highest prestige enrolling a smaller share of disadvantaged students (e.g., Clotfelter 2017). Moreover, students whose parents fall into the top 1% of the income distribution are 77 times more likely to attend highly ranked colleges than students whose parents are in the bottom 20th percentile (Gerber and Cheung 2008; Chetty et al. 2020).

DATA AND MEASURES

Data Sources: College Scorecard and *USNWR* Rankings

To identify the effect of college rankings of the enrollment of disadvantaged students, I merge data from two sources: the Department of Education's College Scorecard data set (hereafter, "Scorecard data") and the *USNWR* National College Rankings (hereafter, "Rankings data"). The Scorecard data span 1997–2015 and integrate information from the Integrated Postsecondary Education Data System,[4] National Student Loan Data System, and the Department of Treasury. The data set includes information on an average of 7,011 colleges per year (for a total of 133,201 college years). Most information from the Scorecard data set only apply to colleges eligible to receive Title IV support (federal financial aid), which represents 85% of all colleges in the United States (Radwin et al. 2013). Fortunately, all colleges featured in the Rankings data are eligible to receive Title IV support and are therefore in the sample.

The Rankings data are based on information from the *USNWR*. The Rankings data were manually retrieved and digitized from historical *USNWR* rankings from library archives. The years 1996–2014 were chosen to match the Scorecard data. Note that the Rankings data lag the Scorecard data by one year, as I model the effects of rankings on outcomes in subsequent years, thus reducing problems of simultaneity. For the purposes of this study, the Rankings data are restricted only to colleges that are nationally ranked. A nationally ranked college is defined by the *USNWR* as an institution that offers a range of undergraduate majors; offers master's and doctoral programs; and emphasizes faculty research. These institutions enroll students from across the United States rather than from just one or two states. There are, on average, 248 such colleges for each of the 19 years in the period of observation, yielding a total sample size of 4,717 college-years.

Not all colleges in the *USNWR* rankings receive numeric rankings. Instead, all colleges are first assigned to one of four tiers, approximately corresponding to the quartiles of the distribution.[5] From 1996 to 2004, only colleges in tier 1 (or approximately the top 50 colleges) were numerically differentiated, while colleges within tiers 2–4 were listed alphabetically. In 2004, colleges in tier 2 became numerically differentiated, and from 2011 onward, tier 3 also received numeric ranks. Colleges within tier 4 are always alphabetically listed. As I describe below, this variation in when colleges became numerically differentiated affords an opportunity to explore the consequences of ranking systems.

[4] The Scorecard data include 1996, but most measures are missing for this year, and I exclude it from analysis.

[5] Because the rankings allow for ties, the number of colleges in each tier can vary slightly from year to year.

Measures

To capture the accessibility of higher education opportunities for students from disadvantaged backgrounds, I rely on two primary outcomes. The first outcome variable is the share of students who receive Pell grants for each college, for each year. Pell grants are a form of need-based federal financial aid, and the share of Pell recipients serves as a measure of the proportion of low-income students in a college (see Delisle 2017). As a robustness check, I also include as an outcome the proportion of students with an adjusted household income of less than $30,000 on the Free Application for Federal Student Aid (FAFSA). Note that this is about 2.56 times the 2016 federal poverty line ($11,700). An absolute cutoff of $30,000 is a crude measure that does not adjust for regional differences in cost of living. However, a disaggregated distribution of student household incomes is unavailable on the Scorecard data for privacy purposes. The second outcome is based on the share of federally aided students at the college who report that none of their primary caregivers graduated from college ("first generation").

These outcomes are conditional on filing the FAFSA. About 40% of all college-going students do not file the FAFSA nationally (Radwin et al. 2013). This is a data limitation because these outcomes are proportions, and the denominator thus only includes students who filed a FAFSA rather than all degree-seeking undergraduate students. To ensure comparability across colleges, I multiply these proportions by the total size of the FAFSA filing cohort and change the denominator to all degree-seeking undergraduate students. This transformation makes the outcomes comparable: instead of being the share of Pell recipients among students who filed a FAFSA, it now reflects the share of Pell recipients across all degree-seeking undergraduates. Moreover, although the outcomes fail to account for students from disadvantaged backgrounds who did not fill out the FAFSA, this omission means the analyses will produce conservative estimates.[6] Finally, the adjusted Pell and first-generation outcomes are missing for 57 and 55 college-years, respectively, and missing data account for 1.22% and 1.27% of cases, respectively.[7]

Five other measures serve as covariates throughout the analyses. These are time-varying characteristics that predict both a college's ranking and its enrollment of disadvantaged students: the total number of degree-seeking undergraduates attending the institution in each year; the admissions rate that colleges self-reported during each year; the average SAT scores of admitted students for each year; the four-year completion rate of the college;

[6] For instance, students who are undocumented immigrants generally do not file the FAFSA, as they are ineligible for federal financial aid.

[7] These cases are missing primarily because College Scorecard suppresses values due to privacy concerns when the number of students involved is too low.

TABLE 1
Descriptive Statistics of the Sample

Variables	Mean	SD	Min	Max
Main outcomes:				
Share of Pell student enrollments (%)	23.90	9.922	4.419	99.01
Share of first-generation student enrollments (%)	24.05	11.35	2.352	99.22
Main covariates:				
Admissions rate (%)	63.8	19.0	5.04	100
Average SAT score	1,149	113.8	760	1,545
No. of first-time, degree-seeking undergraduates (in 1,000s)	19.30	9.71	.142	59.18
Four-year completion rate (%)	62.1	16.9	7.83	97.9
No. of applicants (in 1000s)	17.48	11.52	.023	86.54

Note.—$N = 4{,}717$; each observation corresponds to a college in a given year from 1997 to 2015.

and the number of students applying to each college. Each of these covariates are time varying, and these variables are summarized in table 1.

ANALYTIC STRATEGY

To test key predictions from the algorithmic trade-offs and positional advantage explanations, I pursue five analyses. First, as a descriptive analysis, the share of Pell recipients and first-generation students enrolled is examined separately by tiers. Because colleges vary widely in their overall enrollments, all calculated proportions are weighted by undergraduate enrollment at each college, for each year. This means that the overall measure represents the share of disadvantaged students enrolled across all colleges in each tier. These descriptive patterns provide a basic point of reference to interpret results from the subsequent analyses.

Second, to test the primary predictions of the algorithmic trade-offs explanation, I leverage the expansion of the rankings in 2004 to assess how the share of disadvantaged students changes when colleges are exposed to numeric rankings. Rather than comparing the difference between the share of disadvantaged students enrolled before and after colleges become ranked, a more robust approach is to further compare this difference with what happened for a set of comparison colleges that did *not* experience this transition (a difference-in-difference strategy). Assuming that the transition and comparison colleges otherwise had parallel trends (also called the common trend assumption), this strategy nets out the effect of confounding factors and estimates the effect of becoming ranked (Athey and Imbens 2006).

There are two possible groups that can serve as comparison colleges: (1) those that were consistently in the numeric rankings even before 2004 ("always-ranked" colleges) or (2) those that were never in the numeric rankings ("never-ranked" colleges). The choice between these comparisons depends on the degree to which the pretransition trends in the comparison group are parallel to the transition group. To examine the validity of this assumption, I compare the differences in trends in the years before 2004 for never-ranked and always-ranked colleges.[8] For ease of interpretation, I plot the coefficients with 90% confidence intervals, which serves as a stronger test of the common trend assumption. The results show that the common trend assumption is only valid when compared to always-ranked colleges, and the subsequent analyses use always-ranked colleges as the comparison group.

The statistical model is as follows:

$$Y_{it} = \alpha_0 + \beta_1 T_i + \boldsymbol{\beta}_2 \mathbf{year_t} + \boldsymbol{\beta}_3 (\mathbf{year}_t * T_i) + \boldsymbol{\beta}_4 \boldsymbol{X}_{it} + \varepsilon_{it}, \tag{1}$$

where outcome Y refers to the share of first-generation students or Pell recipients in college i and year t. The indicator variable T equals 1 for all college i that transitioned into numeric rankings in 2004 and 0 for colleges that were already numerically ranked before 2004. The vector **year** includes indicator variables for each year, thus allowing estimates for each year to vary independently. This is a conservative strategy that avoids assuming a linear, quadratic, or other functional form for the underlying time trend. The matrix $\boldsymbol{X}$ includes time-varying covariates for each college: the total number of degree-seeking undergraduates, admissions rates, SAT scores, retention rates, and applicants. To further control for college-specific features, I demean the outcome by subtracting the overall mean share of Pell recipients or first-generation students enrolled at each college across the observation period. The key set of coefficients in this model is the vector $\boldsymbol{\beta}_3$, which describes the difference in trend between transitioning and comparison colleges for each year. All standard errors are clustered at the college level, such that errors are robust to arbitrary forms of correlation within a college over time.

Third, to test predictions from the positional advantage explanation, I examine whether interorganizational dispersion in the share of disadvantaged students increases after colleges become ranked. If positional advantage increases sorting, we expect that variation in the share of disadvantaged students enrolled across colleges should increase after they become ranked. One straightforward measure of dispersion is variance in the share of disadvantaged recipients enrolled across colleges, and I conduct an F test of the equality of variances among colleges comparing the four years before and after they become numerically ranked. Levene's test of

[8] Supporting information and details about this and subsequent analyses can be found in the online appendix.

variances, which accounts for nonnormality in the distribution of variables, is conducted as a robustness check (Levene 1960; Brown and Forsythe 1974). Additionally, if the positional advantage explanation is true, we should expect greater reductions in the share of disadvantaged students enrolled in colleges in the top half of tier. To test this claim, I repeat the difference-in-difference analyses for colleges in the top half of the tier versus the bottom (splitting by the median). Before 2004, colleges ranked between 50 and 126 were tier listed. In 2004, these colleges were differentiated by numeric rank, with some in the top half of the tier (ranks 50 to 87) and others in the bottom (ranks 88 to 126).

Although tests of differences in dispersion and subgroup analyses are informative, the positions of the colleges are not randomly assigned. This is problematic because colleges in the bottom or top half of a tier are ranked in these positions for reasons that are correlated with the enrollments of disadvantaged students. To address this issue, I leverage the design of tier cutoffs in the rankings. The *USNWR* categorizes the top 50 ranked colleges as "tier 1" colleges, while colleges just below the top 50 cutoff are labeled "tier 2." Colleges just above and below the top 50 cutoff are nearly identical, but some are assigned to a more advantageous category while others are not. A theory of positional advantage predicts that a college just above the tier cutoff, and thereby labeled as occupying a better tier, will enroll fewer disadvantaged students relative to colleges just below the cutoff (occupying a lower tier).

This regression discontinuity strategy relies on a series of formal assumptions (Imbens and Lemieux 2008). For brevity, details regarding the regression discontinuity design and evidence to support each of these assumptions, including continuity of the outcome across cutoffs, choice of bandwidths, and functional forms, are discussed in the online appendix. For this analysis, I limit the sample to the period between 2004 and 2014, as colleges under tier 1 did not receive numeric ranks until this period. Because outcomes are responses to the previous year's rankings, all other variables are lagged. To compare within each year, I include year fixed effects in all regression discontinuity analyses. Most importantly, the proportion of low-income or first-generation students enrolled in the prior year is included as a covariate. This is important because enrollments of disadvantaged students for a college in year $t + 1$ depend on the proportion enrolled in year t. Colleges are repeatedly observed in this sample, and in many years the same colleges fall just below or above the cutoff. A comparison of raw differences fails to account for situations where a college under the tier 1 cutoff *already* reduced its share of low-income or first-generation students in the prior year. This adjustment enables the results to represent the average effect of being ranked below the tier 1 cutoff on the share of disadvantaged students enrolled in the following year. Finally, covariates like the total number of undergraduates at each college, number of applicants, and retention rates are included. As usual, because colleges are observed multiple times, I adjust standard errors for clustering at the college level.

Fourth, as a further test of both the positional advantage and algorithmic trade-offs arguments, I conduct mediation analyses. A positional advantage argument posits that reductions in the share of disadvantaged students are driven by increases in applicants to the college. An algorithmic trade-off argument, by contrast, posits that any reductions in the share of disadvantaged students should be driven, at least in part, by attempts by colleges to optimize on their ranking criteria, such as student test scores. To test these hypotheses, I conduct mediation analyses with sensitivity analyses to estimate how much the effect of ranking pressures was transmitted through applicants or standardized test scores (Imai, Keele, and Tingley 2010). The quantity of interest is the ACME or *average causal mediation effect*, which captures the size of the mediated effect.

Fifth and finally, I examine the effect of being unranked relative to being tier listed. The foregoing analyses examine the effect of being numerically ranked relative to being listed in a tier. This is an incomplete test of the effect of being ranked, as it neglects the effect of being listed in a tier relative to being unranked. Research suggests that the effect of being included in a ranking category is theoretically distinct from being numerically differentiated within the category. Exposure to rankings is usually described as a form of commensuration that erases categorical differences between organizations within a ranking system (see Espeland and Stevens 1998). The very same process, however, solidifies differences between organizations that are inside the boundaries of the category and those that are outside. Membership in this category entails a shared system of how good and bad organizations ought to perform (Zuckerman 1999; Hsu, Hannan, and Koçak 2009). As such, mere categorization in the rankings, even if it does not entail numeric differentiation, may also affect the enrollments of disadvantaged students.

The matching analysis compares a balanced set of colleges that are unranked versus those that were categorized as nationally ranked colleges (Rosenbaum and Rubin 1983).[9] As is customary in matching analyses, some nationally ranked colleges may differ so fundamentally from colleges outside the national rankings that no matches can be found. As such, the estimates from matching only apply to colleges in the region of common support. The results are therefore not based on all colleges categorized in the national rankings but only on those that can be matched. As with the above analyses, covariates are included, and standard errors are clustered at the college level.

[9] Details on the construction of this matched set are located in the online app. D, with diagnostics showing balance across major college characteristics after matching.

RESULTS

Overall Trends

What is the overall relationship between rankings and the enrollments of disadvantaged students? Figure 1 reveals that colleges in better tiers consistently enroll fewer Pell recipients as a proportion of their undergraduate population. Moreover, the share of Pell recipients enrolled among colleges in tiers 1 and 2 converged across time, becoming statistically indistinguishable after 2004. By contrast, gaps between tiers 3 and 4 widened between 1997 and 2015. Whereas colleges in tiers 3 and 4 had effectively the same proportion of Pell grantees in 1997, this gap widened to over 10 percentage points in 2014.

One striking trend is an overall increase in the share of Pell recipients across all colleges until 2010. This trend is attributable to increases in federal funding for Pell Grants, which is plotted in figure 2. Pell funding steadily increased from \$7 billion in 1994 to \$15 billion in 2006 (inflation adjusted for 2015 dollars). From 2006 to 2010, Pell funding more than doubled to \$39 billion before declining to \$28 billion in 2014. As expected, this trend in funding predicts the increasing share of Pell recipients for all tiers. However, consistent with research showing increasing horizontal stratification among top-ranked versus lower-ranked colleges (Goldrick-Rab 2016; Clotfelter 2017), the increase in Pell recipients has been more pronounced in lower-tier colleges.

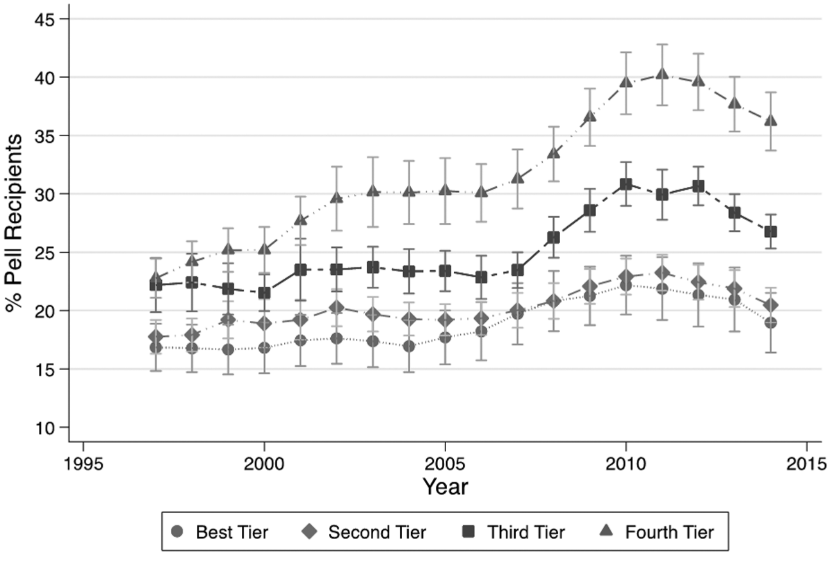

FIG. 1.—Share of Pell recipient enrollments, by year and by tier; 95% confidence intervals shown. Outcomes weighted by number of degree-seeking undergraduates for each school year. Data from USNWR Rankings & College Scorecard, 1997–2015.

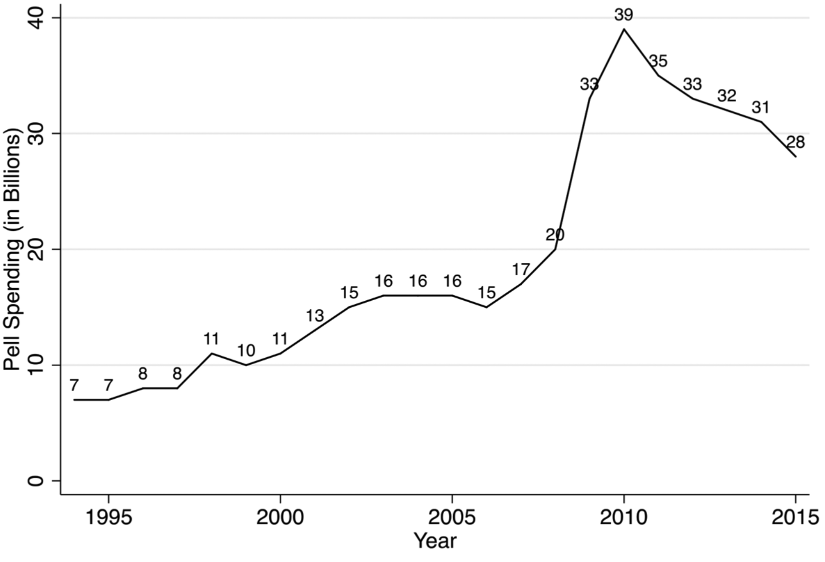

FIG. 2.—Overall federal Pell spending trends; data are from Baum et al. (2016).

The patterns for first-generation students are plotted in figure 3. These trends are substantively similar to those for Pell recipients. Colleges in better tiers enroll a smaller share of first-generation students, and the tiers have spread further apart. Colleges in tiers 1 and 2 now appear similar in their share of first-generation student enrollments, diverging from the trends for tier 3 and 4 colleges.

The fact that better-ranked colleges enroll fewer disadvantaged students is consistent with claims about positional advantage. This descriptive analysis does not, however, test the key prediction of the algorithmic trade-offs explanation, as it does not examine whether exposure to rankings reduces the enrollments of disadvantaged students among colleges on average. Moreover, it remains unclear whether ranking systems caused these descriptive patterns. By design, ranking systems capture many characteristics about colleges, and these trends may instead be the outcome of alternative factors. The following results address each of these limitations in turn.

The Effect of Becoming Ranked on the Enrollments of Disadvantaged Students

The difference-in-difference results support the primary prediction of a theory of algorithmic trade-offs: exposure to rankings led to reductions in the share of disadvantaged students. The coefficients of interest and 95%

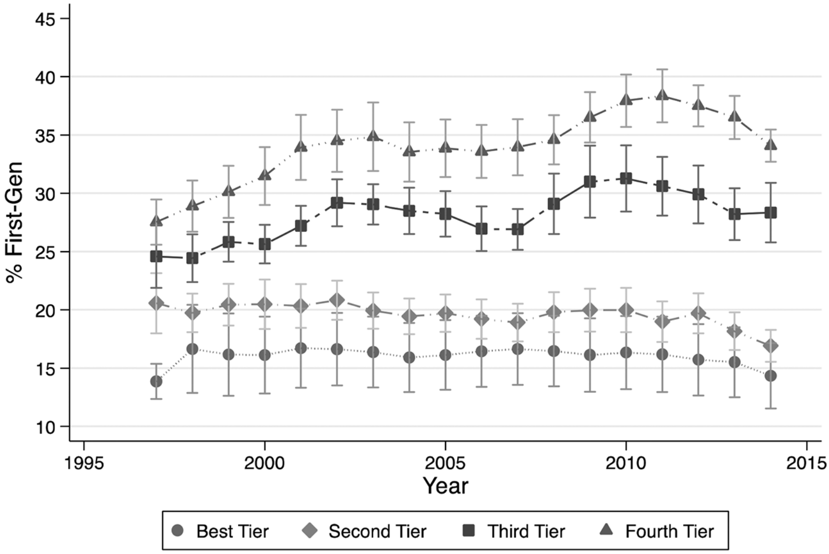

FIG. 3.—Share of first-generation enrollments, by year and by tier; 95% confidence intervals shown. Outcomes weighted by number of degree-seeking undergraduates for each school year. Data are from USNWR Rankings & College Scorecard, 1997–2015.

confidence intervals are plotted in figure 4. The results support the common trend assumption, as none of the coefficients of interest are statistically significant from zero before or on 2004. In 2005, exposure to rankings reduced the share of Pell and first-generation students enrolled by 0.71 ($P = .122$) and 0.69 percentage points ($P = .086$), respectively. By 2006, exposure to the rankings reduced the share of Pell and first-generation students by 1.40 ($P = .009$) and 0.99 ($P = .024$) percentage points, respectively.[10] Moreover, the results are durable. Even by 2015, the differences are still statistically significant ($P < .01$).

Note that these analyses estimate the effect of moving from being alphabetically listed in a tier (i.e., "tier listed") to numerically ranked, which is an intermediate step from being unranked to numerically ranked. For this reason, the difference-in-difference results are likely underestimated, and the matching analyses below are meant to estimate the effect of moving from being unranked to tier listed. Furthermore, there could be spillover effects. For instance, administrators in tier 1 colleges perceived greater competition when tier 2 colleges were added to numeric rankings (see Sharkey and Bromley 2015). This further implies that the difference-in-difference results are

[10] The results for the <$30K outcome are shown in the online appendix, and the results are consistent with the Pell and first-generation outcomes.

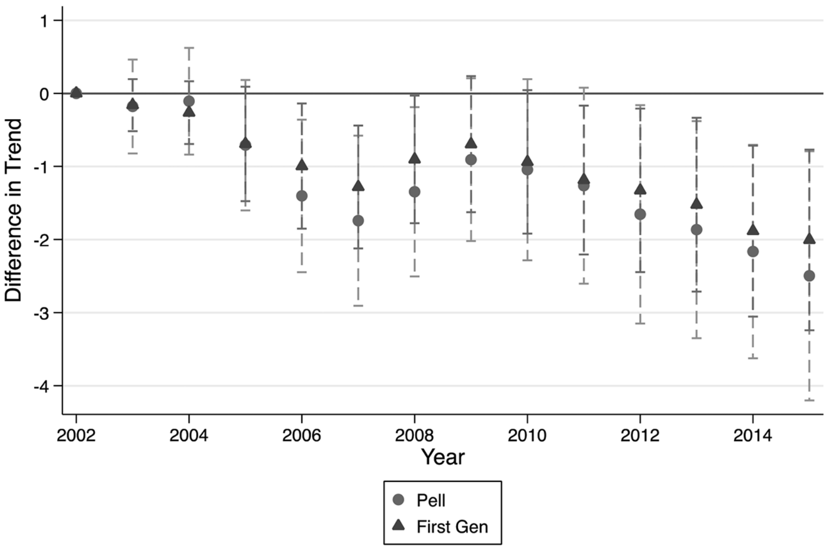

FIG. 4.—Difference-in-difference estimates of effect of entering rankings on share of Pell and first-generation enrollments. Error bars indicate 95% confidence intervals; 2002 is the reference group.

conservative estimates. After all, if the comparison colleges were also reducing their enrollment of disadvantaged students, this spillover effect decreases the effects measured in the present study.

Heterogeneous Effects in Exposure to Rankings

Do the results support the primary predictions of a theory of positional advantage, that is, increased sorting of advantaged students to higher-ranked colleges and disadvantaged students to lower-ranked colleges? Results show that dispersion, as measured in standard deviations, in the share of enrolled Pell recipients *declined* from 2.27 to 1.19 percentage points before and after colleges transitioned to being ranked in 2004. The null hypothesis that these are equal variances is rejected ($P = .03$; $F = 1.29$, d.f. $= 279$). The same is true for the first-generation outcome, where the standard deviation declined from 4.44 to 1.61 ($P < .001$; $F = 7.62$). These results are robust when using Levene's test of variances (Levene 1960; Brown and Forsythe 1974). In other words, after they entered the rankings, colleges became more similar in the share of disadvantaged students they enrolled. This contradicts a theory of positional advantage, which predicts that the distribution would become less uniform.

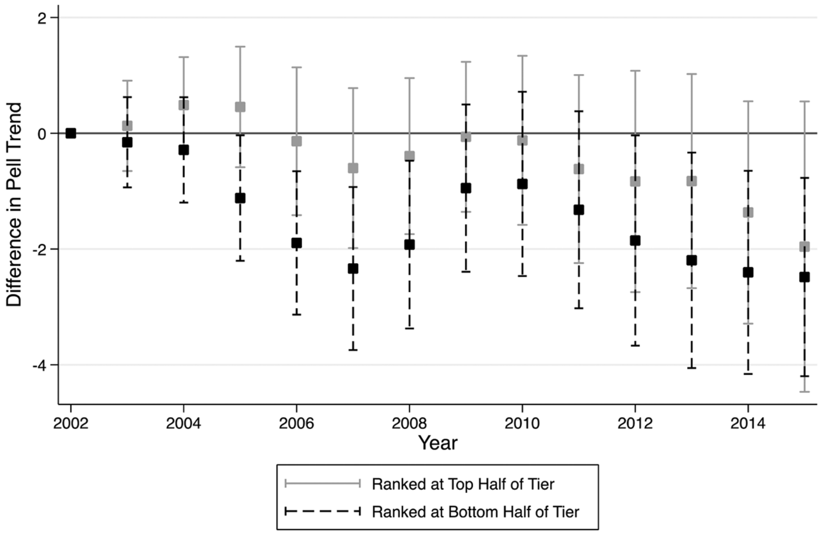

FIG. 5.—Difference-in-difference estimates of effect of entering rankings on share of Pell enrollments, by colleges entering at bottom vs. top half of the tier. Error bars indicate 95% confidence intervals; 2002 is the reference group.

As a further test of positional advantage, figures 5 and 6 decompose the average effects on the share of Pell recipients and first-generation students enrolled by colleges entering at the top versus bottom half of the tier. These trends remain relative to the always-ranked comparison group. The results reveal that the overall decline on the share of Pell and first-generation students enrolled is driven almost exclusively by colleges that occupy the *bottom* half of the rankings. This also explains why colleges became more similar in the share of disadvantaged students enrolled: colleges that entered in lower-ranked positions reduced enrollments of disadvantaged students, converging on the share of disadvantaged students enrolled in higher-ranked colleges. In sum, these results reveal a pattern of asymmetric consequences that run counter to the predictions of a theory of positional advantage.

The regression discontinuity results also fail to support a positional advantage explanation. A visual comparison of the share of disadvantaged students enrolled just above and under the tier cutoff is provided in figures 7 and 8, with the share of Pell recipients and first-generation students plotted as a function of rankings. These figures imply that colleges just *under* the tier 1 ranking cutoff reduce the share of Pell recipients or first-generation students enrolled in the following year by 5.5 or 9.4 percentage points, respectively. As noted above, these raw results are inflated because they do not account for repeated measures, and the adjusted results are shown in

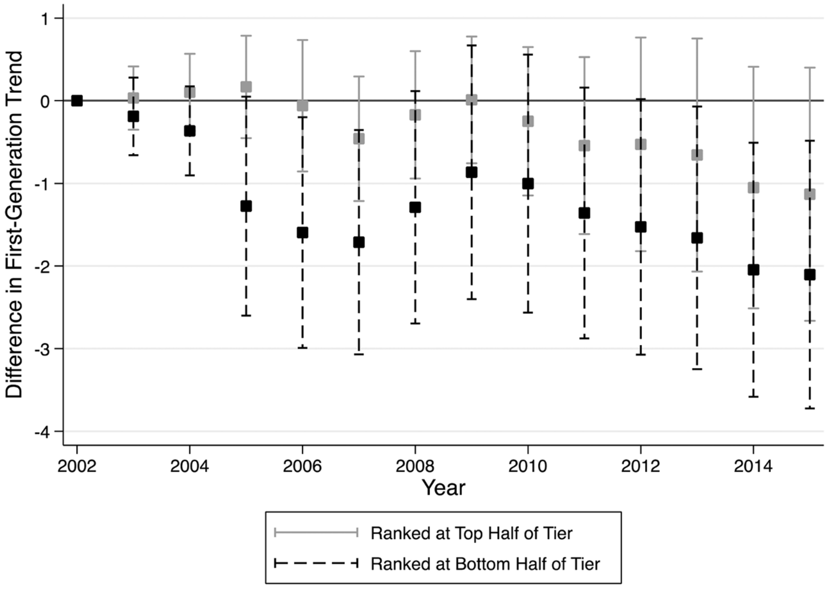

FIG. 6.—Difference-in-difference estimates of effect of entering rankings on share of first-generation enrollments, by colleges entering at bottom vs. top half of the tier. Error bars indicate 95% confidence intervals; 2002 is the reference group.

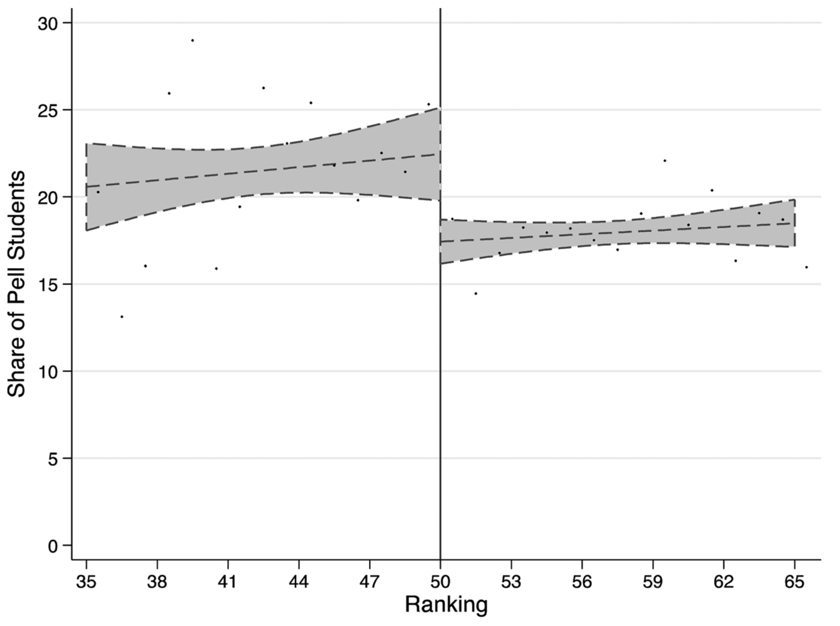

FIG. 7.—Visual representation of regression discontinuity for share of Pell enrollments at tier 1 cutoff.

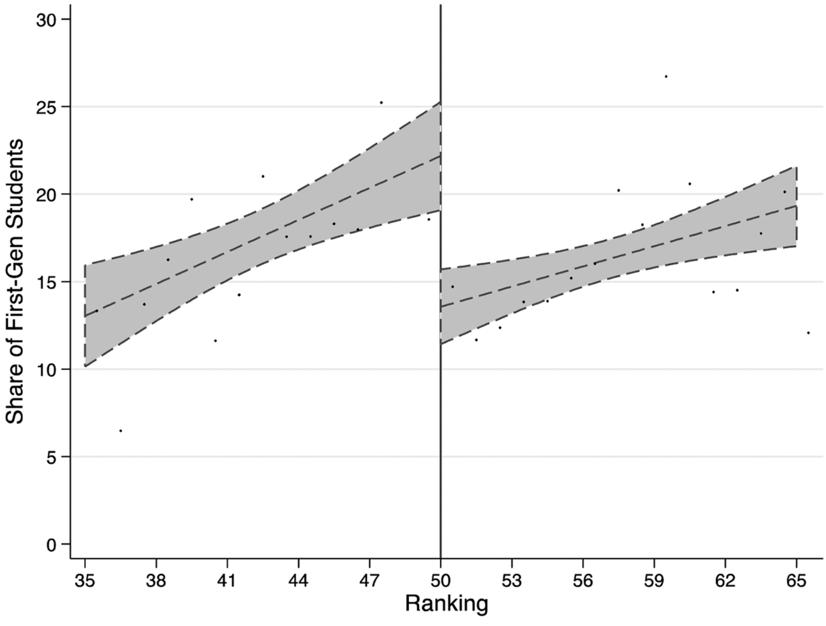

FIG. 8.—Visual representation of regression discontinuity for share of first-generation enrollments at tier 1 cutoff.

table 2. The results show that, at a bandwidth of 15, being *under* the cutoff reduces the share of Pell recipients (in the following year) by 1.01 percentage points (P = .09). The average share of Pell recipients enrolled in this sample was 19.6%, so this effect size corresponds to a 5.3% decline in the share of enrolled Pell recipients. Similarly, being under the cutoff reduces the share of enrolled first-generation students by 1.6 percentage points (P = .005). This corresponds to a 9.2% decline, as the average share of first-generation students enrolled is 17.3%. Whether the bandwidth shifts to 10 or 20, the effects for the first-generation outcome remain statistically significant. For the Pell outcome, however, the effect is no longer statistically significant at different bandwidths. As such, the regression discontinuity analysis implies that being ranked just under the tier 1 cutoff led colleges to reduce the share of enrolled first-generation students, but the evidence is mixed for the share of Pell recipients enrolled. Even so, the evidence as a whole contradicts the key predictions from the positional advantage argument, which posits that organizations that are ranked in more advantageous positions are more likely to experience declines in their enrollments of disadvantaged students.

TABLE 2
Regression Discontinuity Results: Effect of Being under Tier 1 Cutoff on Share of Pell and First-Generation Students Enrolled, across Bandwidths

	Bandwidth					
	10	15	20	10	15	20
	% Pell			% First Generation		
Ranked in second tier (1=yes)	−.379	−1.010*	−0.841	−1.200*	−1.603***	−1.466**
	(.616)	(.569)	(.545)	(.625)	(.544)	(.674)
Rank	−.0132	.0366	.0237	.0299	.0687**	.0600*
	(.0551)	(.0294)	(.0227)	(.0672)	(.0260)	(.0325)
Lagged dependent variable	.947***	.900***	.902***	.890***	.900***	.930***
	(.0261)	(.0407)	(.0329)	(.0314)	(.0277)	(.0197)
Controls added?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Constant	.334	1.044*	1.087**	.319	.508	.649
	(.698)	(.549)	(.469)	(.588)	(.494)	(.591)
Observations	239	344	458	238	343	457
R-squared	.905	.906	.907	.953	.953	.938

Note.—Robust SEs, adjusted for clustering at the college level, are in parentheses.
*** $P < .01$.
** $P < .05$.
* $P < .1$.

Mediation Analyses

The mediation results also contradict a positional advantage argument. Figure 9 shows that the number of applications received at a college is not a statistically significant mediator. Relative to being just under the tier 1 cutoff, colleges above the tier 1 cutoff receive 1,030 more applications in the following year ($P = .679$). This is not a statistically significant effect. Moreover, this increase in applicants does not lead better-ranked colleges to reduce their enrollments of disadvantaged students (as the positional advantage argument would predict). In fact, each additional 1,000 applications a college receives leads to a 0.033 ($P = .024$) and 0.023 ($P = .04$) percentage point *increase* in the share of Pell and first-generation students enrolled. The estimated ACME of the mediation pathway is not statistically significant and is modest in magnitude (.03 and .021 for the Pell and first-generation outcomes, respectively).

To be sure, these mediation results do not rule out all applicant-driven explanations. In particular, the measure of applicants used in the mediation analyses above does not account for heterogeneity by socioeconomic background, and one possible explanation for the results is that colleges under the tier 1 cutoff received fewer applications from students of disadvantaged

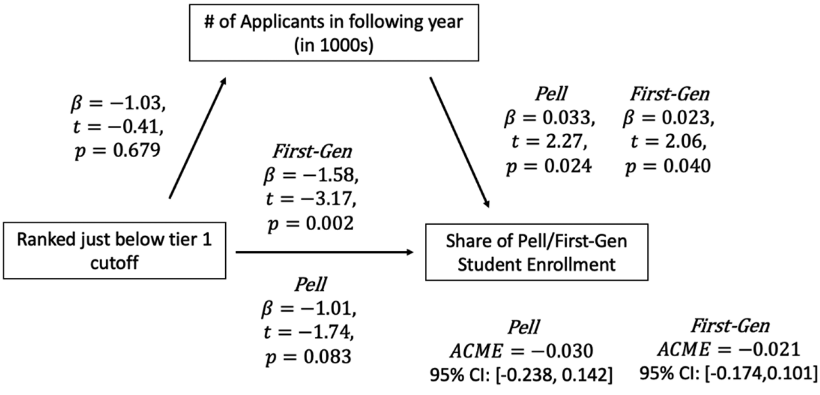

FIG. 9.—Results of mediation analysis for applicants. The sample includes only colleges 15 ranks before and after the tier 1 cutoff, $N = 344$. The ACME quantifies the effect that is transmitted through the mediator and is calculated using simulations per Hicks and Tingley (2011).

backgrounds. Heterogeneous application behavior could mediate the results if exposure to rankings caused students from more advantaged backgrounds to selectively apply to lower-ranked colleges and/or disadvantaged students to selectively apply to higher-ranked colleges. These particular possibilities seem unlikely, as prior research shows that students from more advantaged backgrounds tend to apply to higher-, rather than lower-, ranked colleges (e.g., McDonough et al. 1998).

By contrast, the algorithmic trade-offs argument is supported by the mediation results. Figure 10 reveals that being under the tier 1 cutoff led colleges to admit students with better SAT scores, resulting in a 42.7-point *increase* in average SAT scores the following year ($P < .001$). In turn, each unit increase in SAT scores reduced the share of Pell recipients by 0.12 percentage points ($P < .001$). The average causal mediation effect is −0.53, with estimated 95% confidence intervals between −0.94 and −0.22, meaning that the mediation effect is statistically significant. Because the direct effect is no longer statistically significant, the results also suggest that the effect on the share of Pell recipients enrolled is mediated nearly completely by optimization on student test scores. The same patterns hold for the first-generation outcome, where each unit increase in SAT scores reduced the share of first-generation students by 0.015 percentage points ($P < .001$). The ACME for the share of first-generation students enrolled is −0.639 percentage points, with a 95% confidence interval between −1.06 and −0.307. Moreover, sensitivity analyses suggest that a confounding variable would have to explain 14.7% of the remaining variance before the ACME would be zero.

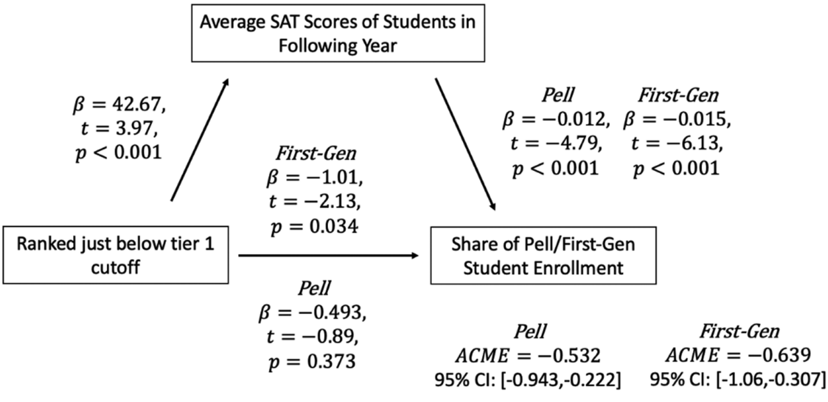

FIG. 10.—Results of mediation analysis for average SAT scores. The dotted line denotes that the relationship is not statistically significant. The sample includes only colleges 15 ranks before and after the tier 1 cutoff, $N = 344$. The ACME quantifies the effect that is transmitted through the mediator and is calculated using simulations per Hicks and Tingley (2011).

Are These Categorical or Numeric Effects?

The results, taken as a whole, support an algorithmic trade-off argument and contradict the positional advantage argument. As a final analysis, I examine the effect of being tier listed, relative to being unranked, on college enrollments of disadvantaged students. The matching results show no statistically significant differences between colleges inside versus outside of the national rankings. When reweighted to balance across propensity scores and when comparing only within the region of common support, being nationally ranked reduces the share of Pell and first-generation students enrolled by 0.004 and 0.5 percentage points, respectively (table 3, first and second columns). These modest differences are not statistically significant, implying that being categorized in the national rankings is, on its own, insufficient to lead colleges to trade off their efforts to provide access to disadvantaged students.

As a robustness check, the same matching approach is repeated to test for differences between colleges that are tier listed versus numerically ranked. This comparison between matched colleges that are tier listed versus numerically ranked should result in statistically significant differences if the difference-in-difference results are robust. Indeed, the shares of Pell recipients and first-generation students are, respectively, 0.831 ($P < .001$) and 0.544 ($P = .027$) percentage points lower in numerically ranked colleges when compared to matched colleges that are only tier listed. In sum, the matching results support the difference-in-difference analyses and furthermore suggest that numeric differentiation, rather than inclusion in the category of

TABLE 3
PROPENSITY SCORE MATCHING RESULTS

	% Pell	% First Generation	% Pell	% First Generation
Listed in tier vs. outside national rankings	−.004	−.504		
	(.318)	(.378)		
Numerically ranked vs. listed in tier			−.831***	−.544**
			(.196)	(.243)
Lagged dependent variable	.909***	.855***	.949***	.917***
	(.0194)	(.0222)	(.0322)	(.0222)
Controls added?	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes
Constant	14.44***	18.34***	10.20**	8.091
	(2.939)	(3.015)	(4.307)	(6.125)
R-squared	.923	.892	.915	.893

NOTE.—Robust SEs, adjusted for clustering at the college level, are in parentheses. Estimates in matched sample only include colleges in region of common support.
*** $P < .01$.
** $P < .05$.
* $P < .1$.

being nationally ranked, drives colleges to trade off access for disadvantaged students.

DISCUSSION AND CONCLUSION

This article articulates two theoretical possibilities for when and how organizational ranking systems might exacerbate existing inequalities between socioeconomic groups. Drawing on the case of *USNWR* college rankings between 1997 and 2015, key implications of these two theories were tested using quasi-experimental research strategies. The algorithmic trade-offs argument predicted that prominent rankings would lead colleges to optimize on criteria that were in tension with serving individuals from disadvantaged backgrounds, leading to an average reduction in the share of disadvantaged students enrolled. The evidence supports this view: exposure to rankings led colleges to reduce their share of enrolled Pell grant recipients and first-generation students, and mediation analyses suggest that this was driven by optimization on student test scores.

The positional advantage argument predicted that exposure to prominent rankings would shift applicants from lower-ranked to higher-ranked colleges. The theory predicted that this would subsequently lead to greater sorting, where higher-ranked colleges would begin to enroll more individuals from advantaged backgrounds and lower-ranked colleges would begin to enroll more individuals from disadvantaged backgrounds. Although this pattern of sorting was evident in the descriptive results, it was not caused by the rankings. In fact, the results show that exposure to rankings reduced sorting, as lower-ranked colleges began enrolling fewer disadvantaged students to meet the level of higher-ranked colleges.

Why would lower-ranked colleges be more likely to reduce their enrollments of disadvantaged students? I conjecture that organizations that enter in lower-ranked positions must take more action to avoid falling further behind than organizations in advantaged positions must take to maintain their positions. This is because rankings shift resources and attention away from lower-ranked toward higher-ranked organizations. Efforts to avoid falling in the rankings lead lower-ranked organizations to divert comparatively more of their scarce resources to optimizing on the rankings. This in turn leads to a reduction in the share of disadvantaged students enrolled. This conjecture is, in essence, a theory about the heterogeneous effects of algorithmic trade-offs, and it is consistent with recent work showing that organizations paradoxically charge higher prices when they are threatened with lower-status positions (Askin and Bothner 2016).

Substantive Magnitude of Effects

Before discussing the theoretical implications of these findings, it is important to interpret their substantive significance. How many low-income and first-generation students would have been enrolled in the absence of the rankings? Between 1997 and 2015, an average of 24.1% and 25.3% of students in nationally ranked colleges were classified as Pell or first generation, respectively. The difference-in-difference results imply that, on average and for each year, exposure to rankings led to a 1.51 and 1.22 percentage point decrease in the enrollments of Pell recipients or first-generation students, respectively. This translates to a 6.3% or 4.8% decrease in the share of Pell recipients or first-generation students enrolled. To contextualize this with raw numbers and with a lower-bound back-of-the-envelope estimate, I assume that exposure to rankings had no effect for colleges *except* for those transitioning in 2004. This estimate implies that these colleges would have enrolled 17,200 more Pell recipients and 13,900 more first-generation students each year, had the colleges not been subject to the rankings. In the 11 years between 2005 and 2015 (inclusive), this adds to nearly 189,200 Pell recipients or 152,900 first-generation students who would have otherwise been enrolled in these colleges.

Where did these students go, if they did not attend the nationally ranked colleges in this study? One possibility is that they did not attend any college. A more likely possibility is that they attended regional or community colleges. These are valuable educational opportunities, but this pattern of results still implies increasing inequality, where disadvantaged students are less likely to benefit from the social and cultural capital that is often gained through attending nationally ranked colleges. Moreover, although attending less selective colleges may yield positive outcomes for some low-income students, research shows that the returns to selectivity in a college are, on average, greater for lower-income students (Dale and Krueger 2002).

Limitations and Opportunities for Future Research on Rankings

For an article that challenges the neutrality of a quantitative device in representing the world, it is also important to highlight the limits of the quantitative techniques used in the analyses. The two theories tested in this study imply that rankings have independent consequences beyond what would be expected in their absence. An ideal analysis would therefore compare outcomes in a world with and without rankings. Because we lack data from such a historical counterfactual, quasi-experimental research designs are the closest approximation available to isolate the rankings from the dynamics that they represent. Each analysis has its own limitations: the difference-in-difference results are limited to the colleges that transitioned in 2004; regression discontinuity results apply only to colleges at the cusp of tiers; and matching results apply only to colleges in the region of common support. Taken together, however, the analyses offer a more complete assessment of the effects of rankings while testing different core predictions from the proposed theories.

The present study also does not directly measure how exposure to rankings changed specific organizational and consumer practices. A theory of algorithmic trade-offs predicts that colleges would reallocate resources in response to the rankings, but such responses were not directly measured in the present study. For instance, Han, Jaquette, and Salazar (2019) find that colleges primarily send off-campus admissions recruiters to affluent high schools. Future research might identify the extent to which this practice is shaped by exposure to college rankings. Measuring specific practices is also important because college administrators and staff may have different levels of experience and rely on different strategies. Future work could examine whether organizational actors with more experience in navigating trade-offs are able to better buffer and adapt against pressures of external rankings, successfully optimizing rankings while minimizing trade-offs in enrollments of disadvantaged students. A related extension would be to investigate why organizations occupying lower-ranked positions are more susceptible to algorithmic trade-offs. I conjectured that this is because they have a smaller pool of resources, such as attention or financial support. This implies that, all other factors being equal, colleges with more limited operational budgets will be more susceptible to algorithmic trade-offs. Although comparable longitudinal data on college finances are difficult to obtain (e.g., Kim 2018), future work could investigate this claim.

Implications for Educational Gatekeeping

What do these results imply for those making admissions decisions at nationally ranked colleges? Rapidly increasing tuition costs and bribery scandals have led to widespread concern that colleges are failing to extend greater opportunity to people from less advantaged backgrounds. This is likely a fair criticism, but the present analysis suggests that it is incomplete. As with the students they evaluate, these gatekeepers are themselves embedded in a heated status competition. Exposure to rankings focuses this competition along metrics that require gatekeepers to balance efforts to extend opportunity against efforts to maintain or build the standing of their colleges. The gatekeepers are themselves gate kept, and it is testament to the importance of public rankings that the effects are attributable to the metrics used by a midcirculation magazine with no formal authority to regulate colleges. Rankings were not merely neutral cameras that reflected status distinctions; they were also engines that drove colleges to trade off efforts to ensure access to disadvantaged students. Indeed, the results show that rankings encourage trade-offs and externalities that, in the case of higher education, result in macrolevel shifts in the distribution of educational opportunities.

Critically, the results imply that the effects of rankings on the enrollments of disadvantaged students flow more strongly through the actions of organizations rather than applicants. Sociologists have long recognized that individuals from different socioeconomic status backgrounds arrive at the college decision with varying levels of achievement, motivation, and information. This focus on inequalities among students, however, can be complemented by analysis of why colleges sort in the way that they do. For the study of educational stratification, this study illuminates how gatekeeping is a reaction to one form of external evaluation. This implies that attempts to change patterns of educational stratification might also attend to the evaluations that shape gatekeeping practices. For instance, absent broader shifts in how colleges are rated and ranked, colleges are disincentivized to adopt gatekeeping practices that favor students from socioeconomically disadvantaged backgrounds (lest they are outcompeted by other institutions). Scholars and think tanks often evaluate and identify promising programs to increase enrollments of disadvantaged students, many of which are not adopted. Such evaluations are primarily geared toward reducing student-level constraints, but it may be equally important to explore when colleges adopt such programs and the factors that encourage or discourage adoption of such practices.

Limiting Negative Spillover Effects

Moving beyond the case of higher education rankings, these findings also inform theories for how to effectively limit the negative downstream consequences of rankings on important social outcomes. One insight is that the design of ranking systems is an important determinant of these consequences. If rankings introduced positional advantages that increased sorting among colleges, then the underlying criteria and weights of a ranking would have been of less relevance: as long as the ranking shifts consumer demand from lower- to higher-ranked organizations, sorting would likely occur. A theory of positional advantages would have implied interventions that equalize the ability for disadvantaged individuals to attain access to desired organizations, such as existing efforts to increase the availability of college financial aid.

A dynamic of algorithmic trade-offs, however, suggests that the design of rankings is important in shaping what organizations optimize and, by extension, what kind of outcomes they will trade off. The results in this study validate contemporary efforts to change ranking criteria. In fact, *USNWR* recently responded to criticisms of its ranking algorithm by including the percentage of and graduation rate of Pell recipients in its 2019 college rankings, which now account for 2.5% of the ranking algorithm (Morse and Brooks 2018). Whether the modest adjustments in the recent *USNWR* rankings will change the dynamics observed in this article is an important analysis for subsequent work as administrative data become available. It is unlikely that these minor changes to the ranking criteria will markedly change the results observed here. However, efforts to advance competing ranking systems that feature social mobility as a metric of college value, along with other forms of sustained pressure on *USNWR* to reflect the importance of accessibility, could reverse the effects observed here (Chetty et al. 2020).

A theory of algorithmic trade-offs also implies that the specific demands of rankings can be counterbalanced. For instance, I theorized that highly salient affirmative action policies should keep a dynamic of algorithmic trade-offs from reducing accessibility for disadvantaged individuals. As a preliminary test of this claim, I repeat the difference-in-difference analysis on the proportion of African-American and Latinx students enrolled and compare colleges with race-based affirmative action versus those without them. Whether a college has an affirmative action policy is based on data retrieved from College Board, which asked colleges to report whether minority status is considered when making admissions decisions. Colleges that reported any preference to minority status are considered to have affirmative action policies.[11]

[11] Note that affirmative action policies have been challenged in many court cases since the 1990s, and adherence to affirmative action is far from uniform: only 35% of colleges had stated organizational policies for race-conscious admissions (e.g., Hirschman and Berrey 2017). This means there is sufficient variation to compare whether the effects of rankings on the enrollment of minority students differs for colleges with vs. without formal affirmative action policies.

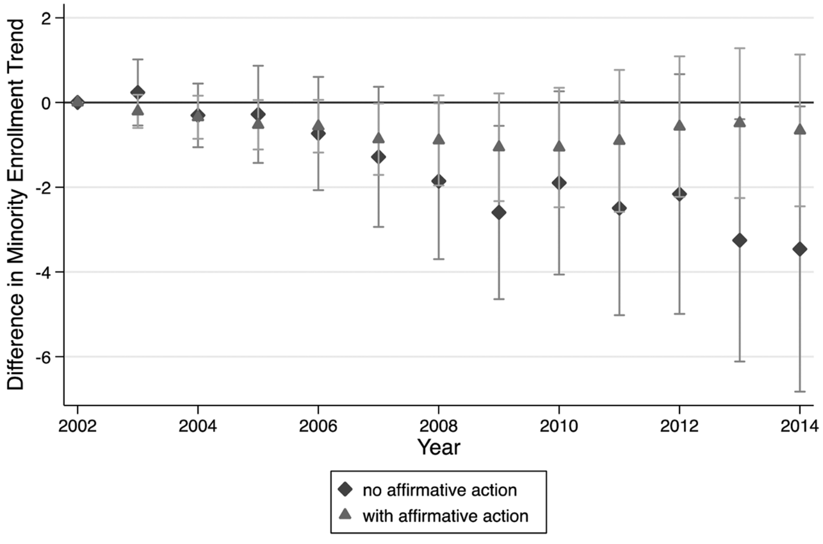

FIG. 11.—Difference-in-difference estimates of effect of entering rankings on share of Black and Latinx enrollments, by presence of race-based affirmative action policies. Error bars indicate 95% confidence intervals. 2002 is the reference group.

The results are shown in figure 11 above. Colleges that did not adopt affirmative action policies show a decline in their enrollments of African-American and Latinx students after 2004, suggesting that exposure to rankings led to algorithmic trade-offs that resulted in declining enrollments of students from these minority groups. Although these changes were not statistically significant from 2005 through 2007, they are part of a broader negative trend. Indeed, in 2008, rankings appear to have reduced the share of African-American or Latinx students in colleges without affirmative action policies by 1.93 percentage points ($P = .042$). By contrast, colleges with stated affirmative action policies did not experience a statistically significant decrease in their enrollments of African-American or Latinx students in any year from 2005 through 2014. In other words, the evidence supports the claim that the adoption of affirmative action policies at the college level forestalled trade-offs in the enrollments of African-American students and other historically disadvantaged racial groups.

These results suggest that similar policies targeted at individuals from disadvantaged backgrounds could plausibly counteract algorithmic trade-offs from reducing access for these groups. Although there is public reprobation when colleges are caught catering to the interests of the rich or failing to ensure access for the disadvantaged, these pressures are diffuse when compared to the rankings. Moreover, current affirmative action policies do not specify the socioeconomic status that students must come from, and colleges are able to satisfy demands for racial affirmative action while still optimizing on their rankings and enrolling fewer low-income or first-generation students. One potential policy intervention that has seen increasing interest from both policy makers and academics, then, is class-based affirmative action that prioritizes the enrollment of low-income and first-generation students (Stevens and Roksa 2012; Ford and Patterson 2018).

Implications for Research on the Effects of Rankings

Taken as a whole, the research advances the literature on rankings more generally. First, the results broadly support existing claims that colleges react to rankings by optimizing on a narrow set of criteria, and that higher-ranked colleges receive more applicants. As noted above, disentangling the effect of rankings from what they represent is empirically difficult, and this research adds to a burgeoning empirical record establishing that rankings do more than just neutrally represent what people perceive as valuable: they can shape both public perceptions and organizational behavior.

Second, the results show how rankings have spillover effects beyond the boundaries of the organizations they evaluate, lending credence to concerns from critical data studies about the negative externalities associated with the expansion of public measures like ranking systems. The research establishes algorithmic trade-offs as a general dynamic, whereby organizations focus on some outcomes at the expense of other valued outcomes. Moreover, I have theorized and demonstrated that, under specific conditions, this dynamic leads organizations to reduce accessibility for disadvantaged individuals. These conditions may hold for other forms of schooling, such as business or law schools. They may also hold for hiring in investment banks or consulting firms—where firms are publicly ranked by Vault according to a methodology that values “firm culture,” “perceived work life balance,” and “employee satisfaction.” These criteria are measured using anonymous surveys given to employees across multiple consulting firms, and firms that seek to optimize on these criteria may be further incentivized to prioritize alignment and “cultural fit” in hiring employees, often at the expense of disadvantaged individuals who lack the cultural capital to demonstrate such alignment (Rivera 2015).

Third, and of equal importance, the results imply that the potential for rankings to contribute to broader inequalities between individuals from advantaged versus disadvantaged backgrounds may be relatively bounded in scope. To be sure, a dynamic of algorithmic trade-offs reduces accessibility of educational opportunities and contributes to structural barriers to social mobility. This is a substantively important outcome. Nevertheless, by formally developing the scope conditions of the theory, this research also suggests that there are many domains where algorithmic trade-offs would not lead to this outcome. As one prominent example, Michelin ratings for restaurants do not contain clear criteria that restaurants can optimize, making it unlikely that algorithmic trade-offs systematically drive certain outcomes over others. By contrast, a theory of positional advantage as a driver of increased sorting between socioeconomic groups is more general than algorithmic trade-offs. The scope conditions for when positional advantages drive increased sorting are broad, capturing the fact that any domain where organizations are evaluated by a popular ranking system and organizational capacity to meet demand cannot be scaled quickly. The fact that evidence in this setting contradicts positional advantage as a driver of inequality suggests that rankings contribute to socioeconomic inequalities only under more specific conditions.

Ultimately, as ranking systems come to order an increasing number of social domains, researchers should continue to investigate how the expansion of rankings and other public measures differentially affects socioeconomic groups. External evaluations are occasionally described as "engines of anxiety" that drive organizations to change their behavior (Espeland and Sauder 2016). This article extends this metaphor: because evaluations simplify the world and cannot fully capture all the features that we care about in an organization, there should be rightful concern about the trade-offs they impose. While ranking systems may be motivated by demands for transparency, efficiency, and accountability, it is just as important to identify when and how they might also serve as engines of social inequality.

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