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College admission as a screening and sorting device*

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Abstract

We study how GPA-based and holistic admission tracks in a centralized college market affect programs' degree completion through the information (screening) and selection (sorting) they generate. We validate a simple partial equilibrium model of program admissions by exploiting admission cutoffs and a reform that relaxed caps on holistic seats. We find that programs choose cutoffs and quotas so that marginal completion is similar across tracks when holistic quotas are slack but higher in the holistic track when they bind. A sorting–screening decomposition shows that at the admission margin most gains from holistic admissions come from self-selection of higher-potential students into the holistic track, with modest screening gains. Programs do not internalize admission externalities, and marginal applicants rejected from the holistic track are about 5 percentage points less likely to complete a degree elsewhere than comparable GPA-track rejects, with gaps in selective programs with small holistic quotas twice as high. Expanding holistic quotas in constrained programs would thus raise total degree completion, and we find that this favors students with weaker academic records and family backgrounds.

JEL-codes: D04; H43; I22; I23; I28; J24

Keywords: College admission, Higher education, Screening, Sorting.

*This is an extensive revision of Gandil and Leuven (2022). This version November 2024. Gandil: ROCKWOOL Foundation Research Unit, also affiliated with CESifo and IZA. Contact: mga@rff.dk. Leuven: Department of Economics, University of Oslo, also affiliated with Statistics Norway, CESifo and IZA. Contact: edwin.leuven@econ.uio.no. We thank Peter Arcidiacono, Nathan Hancart, Hessel Oosterbeek, Sarah Turner, and seminar participants for valuable feedback and suggestions. The Norwegian Research Council supported this research under project no. 275906.

1 Introduction

Universities around the world use different instruments to assign seats in programs with excess demand. Some rank applicants on grades alone; others invest in holistic review; many combine the two. Grade-based rules use a single, verifiable measure that is cheap to produce and easy to compare. Holistic review lets programs evaluate fit, motivation, and field-specific preparation through essays, interviews, tests, and portfolios, but this information is more expensive for applicants to supply, more resource-intensive to collect, and harder to compare. Universities therefore face a trade-off: when screening technologies differ in the information they reveal and the costs they impose, how should they allocate seats across them? The answer shapes who enters higher education, where they enroll, and whether they complete a degree.

We study program choices and their consequences in a centralized market that embeds two admission technologies side by side. Danish bachelor programs admit students to the same program through parallel GPA-based and holistic tracks and make all offers through a nationwide student-proposing deferred-acceptance (DA) mechanism. The GPA track is a standard one-dimensional priority rule; the holistic track allows programs to condition priorities on additional, program-tailored information at the cost of more demanding application portfolios. Applying via the holistic track is therefore both an information channel and a costly signal of program-specific interest. Because we observe all applications, track choices, and subsequent enrollment and completion outcomes for admitted and rejected applicants across the system, we can follow both admits and rejects from each track and provide the first market-wide, head-to-head comparison of GPA-based and holistic admissions for the same programs along a common admission margin.

We make three contributions. First, we develop a model in which each program chooses track-specific admission thresholds and seat allocations to maximize expected completion among its students. The baseline model predicts that optimal program behavior equalizes marginal completion probabilities across the GPA and holistic tracks, and that binding caps on holistic admissions generate higher marginal completion in the holistic track. The model delivers estimands that we identify using fuzzy regression discontinuity designs at program-by-track cutoffs, and we also exploit a reform that relaxed regulatory constraints on holistic quotas to test the model's predictions. In the unconstrained regime, marginal completion rates are very similar across GPA and holistic tracks. Before the reform, constrained programs exhibit substantially higher marginal completion in the holistic track than in the GPA track, and these gaps close once the cap is lifted. These patterns are consistent with programs choosing thresholds and quotas to maximize expected completion among their own students.

Second, we quantify the screening and sorting roles of holistic admissions using a decomposition that separates a sorting component, driven by track-specific application costs and self-selection into the holistic track, from a screening component, driven by additional information beyond GPA. The decomposition is defined at a common admission margin and for a common outcome (degree completion), so that the two components are directly comparable, and we extend it to quantify inframarginal screening. At the admission margin, we find that the benefits of holistic admissions arise primarily through sorting: applicants who choose the holistic track are, on average, more likely to complete a degree than applicants with the same GPA who do not apply through that track. Additional holistic information generates only modest gains in completion beyond what GPA alone would deliver. Away from the admission margin, we find small but positive screening gains, especially in programs that make intensive use of holistic admissions and employ essays, interviews, or tests, but these gains are quantitatively modest relative to the sorting component. At the same time, programs that rely heavily on the holistic track sustain high completion rates with much weaker scope for sorting. This pattern is consistent with programs adapting their use of holistic evaluation to the applicant pools they face.

Third, we quantify externalities of program-level admission decisions by comparing what happens to students who are just admitted versus just rejected in each track, both within the admitting program and elsewhere in the system. This allows us to estimate whether marginal admits would have completed a degree in another program if they had been rejected, and thus how program-level admission choices relate to system-wide completion. We find that while marginal admits have similar completion probabilities within the admitting program regardless of track, marginal applicants rejected from the holistic track are substantially less likely to complete higher education elsewhere than marginal applicants rejected from the GPA track. We estimate that holistic-track admits have value added for college completion roughly five percentage points higher than GPA-track admits, driven almost entirely by the lower completion probability elsewhere among rejected holistic applicants. Value-added gaps are particularly high, over 10 percentage points, in programs that make relatively little use of holistic evaluations. From an aggregate perspective, reallocating seats from GPA to holistic admissions in programs with small holistic quotas would, therefore, raise total degree completion, even though such changes leave completion within those programs largely unchanged. This finding suggests that funding education based on program-completion may cause program incentives to be misaligned with a goal of overall degree-completion. As marginal holistic applicants are from slightly lower socio-economic and academic background, we do not find evidence of a binding efficiency-equity trade-off in college admissions.

Our work relates to several strands of the literature. A first set of studies examines the predictive power of standardized tests and other measures of academic preparation for college performance and completion, and evaluates the incremental value of essays, interviews, and other subjective components of application portfolios (e.g., Burton and Ramist, 2001; Zwick, 2007; Goho and Blackman, 2006; Murphy, Klieger, Borneman, and Kuncel, 2009; Kuncel, Kochevar, and Ones, 2014; Allensworth and Clark, 2020; Beattie, Laliberté, and Oreopoulos, 2018; Kamis, Pan, and Seah, 2023). This literature focuses mainly on screening: given a set of applicants, which information best predicts success? A standard limitation, emphasized by Rothstein (2004), is that outcomes are usually observed only for admitted students. Our setting addresses this concern by observing both admitted and rejected applicants across the higher-education system and following their completion outcomes regardless of where they enroll.

A second strand studies how admission mechanisms affect applicant behavior and sorting, showing that application requirements and costs influence whether and where students apply. Smith, Hurwitz, and Howell (2015) find that essay requirements and fees reduce applications without improving match quality, while Pallais (2015) shows that even small cost changes can have large effects on application behavior. Studies of mandatory entrance exams (Hyman, 2017; Hurwitz, Smith, Niu, and Howell, 2015) and the broader evidence summarized by Dynarski, Nurshatayeva, Page, and Scott-Clayton (2023) highlight the role of non-pecuniary application costs. A growing literature examines test-optional policies in the United States, where applicants can choose whether to submit standardized-test scores under a single admission channel (e.g., Belasco, Rosinger, and Hearn, 2015; Saboe and Terrizzi, 2019; Bennett, 2022; Sacerdote, Staiger, and Tine, 2025). In those settings, the decision to disclose scores is itself a signal. In our setting, upper-secondary GPA is always observed, and programs operate parallel GPA and holistic quotas with different application costs; holistic application does not affect GPA ranking. Institutionally, our setting is also related to Friedrich, Hackmann, Kapor, Moroni, and Nandrup (2024), who study how Danish medical schools respond to information held by rival programs and students. They focus on strategic interactions and "home bias" in admissions, whereas we focus on the roles of capacity, screening, and sorting within programs. Avery and Levin (2010) and Lee (2009) provide related evidence that early admission programs and preference signals help colleges manage application risk.

A third strand considers allocation mechanisms, application architectures, and match quality. Much of this work studies the effects of selectivity and affirmative action in higher education (e.g., Arcidiacono, Lovenheim, and Zhu, 2015; Arcidiacono and

Lovenheim, 2016; Bleemer, 2022) and the properties of centralized assignment mechanisms. Avery, Kocks, and Pathak (2025) compare decentralized applications, common applications, and ranked applications in the Boston charter sector. They show that a common application can expand access but also increase competition, while a ranked application based on deferred acceptance can achieve better matches with low application costs. Related work studies the spread of common applications in U.S. higher education (e.g., Knight and Schiff, 2022) and the introduction of affirmative-action constraints in centralized college admissions (e.g., Otero, Barahona, and Dobbin, 2021). The Danish system we study already uses a centralized ranked application with student-proposing deferred acceptance across programs. The margin of interest is within programs, where a separate holistic track with earlier deadlines and richer portfolios creates track-specific application costs. Our results show how such within-program design choices affect screening, sorting, and completion in a centralized market.

Finally, our analysis relates to work that embeds admission thresholds in models of the college market and to studies that combine microeconomic theory with quasi-experimental evidence in education. Structural models of college markets treat admissions, tuition, and financial aid as equilibrium choices of colleges (e.g., Epple, Romano, and Sieg, 2006, 2008; Fu, 2014), and more recent work uses dynamic equilibrium models to study the effects of changes in testing policies on enrollment and completion in decentralized systems (e.g., Borghesan, 2025). Ellison and Pathak (2025) develop a curriculum-matching model in which a school jointly chooses curriculum and student assignments, and show how such behavior can affect the interpretation of regression discontinuity estimates at exam-school cutoffs. Our approach is similar in spirit, but we focus on a dual-track admission system in a centralized market and emphasize the screening and sorting roles of parallel tracks with different application costs. We complement work that estimates individual returns at admission cutoffs (e.g., Öckert, 2001, 2010; Hastings, Neilson, and Zimmerman, 2013; Kirkeboen, Leuven, and Mogstad, 2016) by emphasizing that the cutoffs themselves are chosen by programs and that admission decisions can have external effects on completion elsewhere in the system.

The remainder of the paper is organized as follows. Section 2 describes the institutional context and the dual-track admission system. Section 3 presents the theoretical framework and its testable implications. Section 4 describes the empirical strategy and data. Section 6 documents how programs use the two tracks and presents the regression discontinuity estimates, and Section 8 develops and implements the sorting–screening decomposition. Section 9 concludes with implications for the design of admission systems.

2 Institutional background

Danish higher education is essentially a public system that is accessible to everyone with a diploma from the academic high school tracks ("Gymnasiale uddannelser"). There are 8 universities, 7 university colleges, and 8 business academies, each with multiple campuses. At entry, higher education offers 3-year bachelor programs and 2- to 4-year professional degrees, and over 90% of bachelor's graduates subsequently complete a master's degree. Programs are defined as a specific field of study at a given institution. Institutions do not charge tuition fees, and students can use a generous public grant and loan system to cover living expenses.

Programs and assessment The Danish funding model combines fixed grants with performance-based subsidies. The majority of funding is based on coursework completion, with additional incentives tied to completion times. This creates strong incentives for programs to admit applicants who are likely to complete their studies.

Programs generally set their own capacities through two admission quotas that differ in their evaluation criteria.[1] All applicants with a high school GPA (or equivalent) are ranked in the main GPA-based admissions exclusively using the high-school GPA. We refer to this admission track as Quota 1 (Q1). High-school GPA is based on a combination of centrally and externally graded exit exams and continuous assessment.[2] In Quota 2 (Q2), applicants are ranked based on holistic evaluations of their applications. Applicants must explicitly apply for assessment in Q2. Both quotas admit students to the same program.[3]

In our main sampling window, 2012–2015, programs were free to choose the share of students to admit through Q2. Before 2012, academic programs were restricted to accepting at most ten percent in Q2. We exploit this policy variation in Section 6.4.

Programs must evaluate and rank all Q2 applicants regardless of the Q2 quota. Only applications directed to the program are observed by its assessment committee, and the program does not know its priority on the applicant's rank-ordered list. In the period we study, programs ranked Q2 applicants internally and the process was not standardized.

Programs can choose and combine evaluation instruments in Q2. Instruments can

[1] A few programs are restricted from increasing capacity, either because of high unemployment among graduates or because the government is a monopsonist employer (e.g., some humanities programs and medicine).

[2] GPA is recorded on a 7-point scale to one decimal place; a lottery number breaks ties on the first decimal.

[3] The quotas were introduced in 1977, when centralized admission was implemented, to ensure that applicants without a high-school degree would also have access to higher education.

Table 1: Applications and rank-order in the deferred acceptance procedure

Application list			Rank-ordered list in DA		
Rank	**Program**	**Q2**	**Rank**	**Program**	**Priority**
1	Econ - Aarhus	✓	1	Econ - Aarhus	GPA
2	Econ - Copenhagen		2	Econ - Aarhus	Q2 ranking
3	Business - Aarhus		3	Econ - Copenhagen	GPA
			4	Business - Aarhus	GPA

Note: The table illustrates how Q2 is handled in the deferred acceptance procedure. The left panel shows an example of an applicant's application list. The right panel shows how the centralized system embeds the Q2 application below the Q1 application for the same program.

be "objective," for example a subset of high-school grades (Grades) or college entrance tests (Tests), or "subjective," for example evaluation of relevant experience (CV), written assignments (Essay), or interviews (Interview). We employ the classification of UFM (2020). Appendix Figure B1 shows that CV, grades, and essays are the most popular instruments and that programs typically use two or three instruments.

The evaluation instruments of a program are known to applicants at the moment of application, but the actual scoring is not, and anecdotal evidence suggests that scoring is informal in assessment committees. From the perspective of applicants, holistic evaluation is therefore a black box, not unlike selective college admissions in the United States (Bastedo, 2021). However, unlike the United States, all programs must report their rankings to a centralized admission office. We are the first researchers to analyze these rankings; during our period, programs most likely treated them as private information.

Applications and offers Applications are submitted through a single online portal managed by a government agency. There are no application fees, and applicants can apply to up to eight programs, which they must rank from most to least preferred.[4]

Applicants who only apply to programs' GPA-based admissions in Q1 must submit their applications before mid-July after the final high-school GPA is known. The application deadline for applicants who also want to be considered in Q2 is in March. The earlier deadline allows programs to assess and rank all Q2 applicants. After the Q1 deadline in July, programs report their rankings of applicants within each quota to the Ministry of Higher Education.

The Ministry computes admission offers based on applicants' rank-ordered lists,

[4]Seventy-five percent of applicants apply to at most three programs, fewer than 10 percent apply to more than five, and only 3 percent exhaust the list, so only a small minority are likely to be constrained by the limit.

programs' quota-specific capacities, and programs' rankings using a deferred acceptance algorithm with multiple tie-breaking (DA, Abdulkadiroğlu and Sönmez, 2003). The algorithm first unrolls the application lists into a rank-ordered list where, for each applicant, all Q2 applications to a program are placed after the default (Q1) application to that program but before the next-ranked program (Table 1).

The DA mechanism yields an allocation that can be represented in terms of quota-specific cutoffs: applicants receive their highest-ranked program–quota for which their eligibility score is above the cutoff (Azevedo and Leshno, 2016). With the expanded list, an applicant is first considered in Q1; if she clears the Q1 cutoff she is admitted in Q1. If she does not clear the Q1 cutoff, she can be admitted in Q2 if she clears that cutoff (given that she applied to Q2). If not admitted to the program in either Q1 or Q2, the applicant is assessed at the next program on her list.

The presence of Q2 does not change the strategy-proof nature of the admission process (apart from the limit of eight programs).[5] Moreover, Q2 does not affect the counterfactual program: offers are computed by the DA algorithm, but all admission offers (to programs, not quotas) are released simultaneously in August, regardless of whether applicants applied or were admitted through Q2.

On the day offers are sent out, the number of applicants admitted and rejected through each quota is published on the Ministry's website. The Q1 cutoffs in terms of GPA are made publicly available and receive front-page coverage. The scoring of applicants (and hence cutoffs) in Q2 is not public, though we observe it in our data.

Figure 1 shows how the share of applicants admitted through Q1, Q2, and to non-oversubscribed programs developed during our period of analysis. Over 40 percent of admitted applicants are admitted based on GPA (Q1), while the share admitted through holistic quotas (Q2) increased from 14 to 25 percent. This reflects stronger competition, as the share admitted to programs that are not oversubscribed has been steadily declining.[6]

3 Theoretical framework

To organize the analysis, we develop a simple model of program incentives. Consistent with our setting, the program earns revenue from student completion and bears both instructional and applicant-screening costs. The model yields testable predictions and

[5]Without Q2 all programs would use the same priority score and the DA mechanism would be serial dictatorship. Bjerre-Nielsen and Chrisander (2022) show that strategy-proofness is maintained in the Danish setup, abstracting from truncation of rank-ordered lists.

[6]Figure 1 reports shares of admitted applicants; our analysis is at the program-application level.

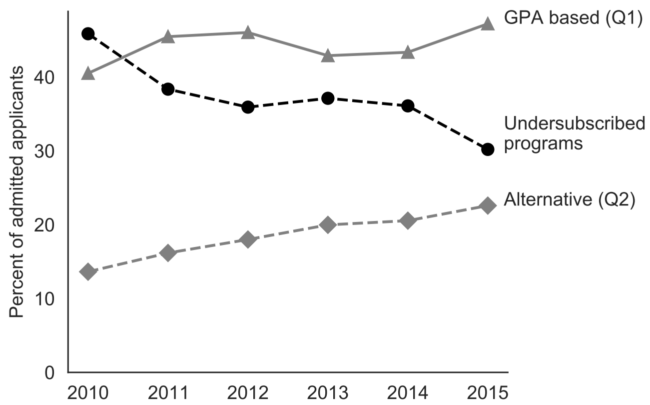


Figure 1: Admitted applicants by admission channel

Note: The figure shows admitted applicants by admission channel. Evaluation only takes place in the mechanism if a program is oversubscribed. Data are computed at the applicant level.

guides our interpretation of the empirical results.

We study a program that faces a mass of applicants normalized to size 1. Every applicant has latent quality $y^1 \in [0,1]$, interpreted as the latent program-completion probability given admission. The program observes y^1 imperfectly through noisy signals. Every applicant sends a GPA signal $r_1 \sim F_1(\cdot \mid y^1)$ for the GPA-based quota (Q1). Applicants can also choose to apply in Q2 ($Q2 = 1$), which then generates a second signal $r_2 \sim F_2(\cdot \mid y^1, I)$. Signals depend on applicant quality and, in the case of r_2, on the screening technology I, which can affect both bias and precision.[7]

The program chooses admission cutoffs, which determine the size of Q1 and Q2. An applicant is admitted if r_1 clears the Q1 cutoff a, or r_2 clears the Q2 cutoff b (if $Q2 = 1$):

$$A = \begin{cases} 1 & \text{if } r_1 \geq a \vee (Q2 = 1 \text{ and } r_2 \geq b), \\ 0 & \text{otherwise.} \end{cases}$$

The program receives funding from program completion and chooses cutoffs to maximize the ex-ante expected quality of admitted students net of admission and screening

[7] Q1 technology is fixed and therefore suppressed in F_1. We assume the signal technologies satisfy the monotone likelihood ratio property such that the expected quality is increasing in the signal. Following Chade, Lewis, and Smith (2014) we assume programs almost always reject very low-quality applicants and almost always accept very high-quality applicants. We expand on the model in Appendix A.2.

costs:

$$\max_{a,b} E[y^1 \mid A=1, Q2=1]\Pr(A=1 \mid Q2=1)\Pr(Q2=1)$$
$$+E[y^1 \mid A=1, Q2=0]\Pr(A=1 \mid Q2=0)\Pr(Q2=0)$$
$$-C(\Pr(A=1)) - SC(\Pr(Q2=1) \mid I),$$

where admission costs $C(\cdot)$ increase in the mass of admitted students and screening costs $SC(\cdot \mid I)$ increase in the number of applicants assessed in Q2 and depend on I. This mirrors the Danish institutional requirement that all Q2 applicants must be assessed.[8]

3.1 Program admissions with inelastic applications

To illustrate the main intuitions we first consider the case when Q2 applications are inelastic with respect to the admission cutoffs. Appendix A.1 shows that programs equate the expected completion rate of marginal admits in each quota to marginal admission cost:

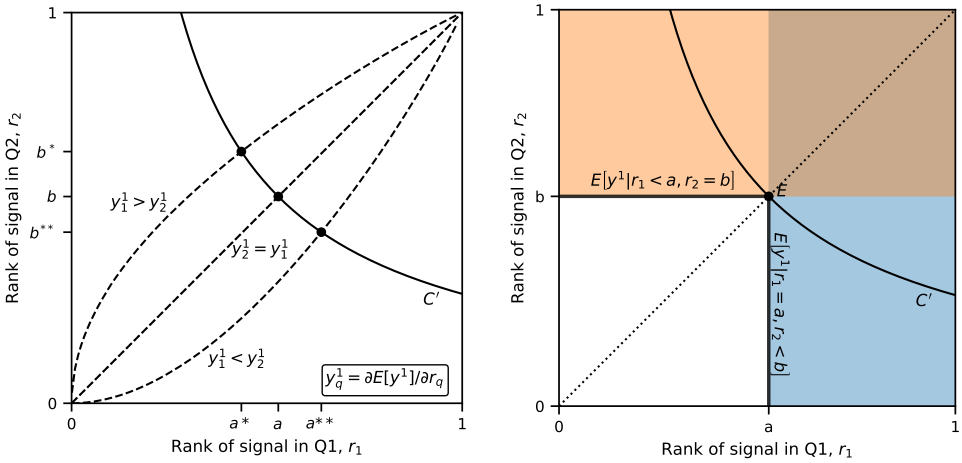
$$\omega E[y^1 \mid r_1 = a, r_2 < b, Q2=1] + (1-\omega)E[y^1 \mid r_1 = a, Q2=0]$$
$$= E[y^1 \mid r_1 < a, r_2 = b, Q2=1] = C', \quad (1)$$

where ω is the share of applicants at the GPA-based admission margin who applied to Q2. The first term is the expected completion rate for marginal applicants in GPA-based admissions ($r_1 = a$), pooling those who did and did not apply to Q2. The second term is the expected completion rate for Q2 applicants at the holistic-admission margin ($r_2 = b$) who do not qualify based on their GPA ($r_1 < a$). Both marginal completion rates are set equal to marginal admission costs C'. With inelastic applications, screening costs are beyond the control of the admission officer.

Figure 2 illustrates the role of screening technology for the case where everyone applies to Q2 ($\omega = 1$). The first-order condition simplifies to

$$E[y^1 \mid r_1 = a, r_2 < b] = E[y^1 \mid r_1 < a, r_2 = b] = C', \quad (2)$$

[8] This admission technology reflects the Danish context with Deferred Acceptance, where programs set capacities, which in a single-program setting is equivalent to setting cutoffs. In the empirical application, applicants above a cutoff do not necessarily get admitted if they are admitted elsewhere, so the cutoff formulation is more natural and leads to an instrumental-variables design to account for non-compliance. We assume that the admission officer takes the screening technology as exogenously given when setting capacity.



(a) Screening technology

(b) Comparison at the margin

Figure 2: Optimal admission policies

Note: The figure shows a simulated example with an interior solution in which applicants are admitted through both Q1 and Q2. Panel (a) shows combinations of cutoffs (a,b) that equalize marginal completion rates across quotas and their intersection with the marginal cost function. Panel (b) shows the corresponding admitted region and quota-specific marginal applicants. See Appendix A.2 for details.

so the completion rates of the Q1 and Q2 marginal admits are equal and both equal marginal admission cost. If one quota had a higher completion rate at the margin, the program could raise profits by shifting seats to that quota.

The noise of quality signals $\partial E[y^1]/\partial r_q$ matters for where the cutoffs are set. In panel (a), the diagonal dashed line shows all cutoffs that equalize marginal completion rates when signals are equally informative in Q1 and Q2. The solid line is the marginal cost function as a function of the share of admitted applicants; its intersection with the envelope of equal-marginal-completion combinations pins down the optimal (a,b). As the Q2 signal becomes noisier, the program lowers the Q1 cutoff and raises the Q2 cutoff, admitting more students based on GPA and fewer based on holistic assessment. In the limit where r_2 is uninformative, no one is admitted through Q2 and admissions are purely based on GPA. The reverse holds when r_1 is less informative than r_2.

Panel (b) illustrates the implied admission region, with the quota-specific marginal applicants highlighted by the solid lines extending from point E. Holistic admissions provide additional information for a given pool of applications, and if this information is predictive of outcomes the program can improve completion. We refer to this mechanism as *screening*.

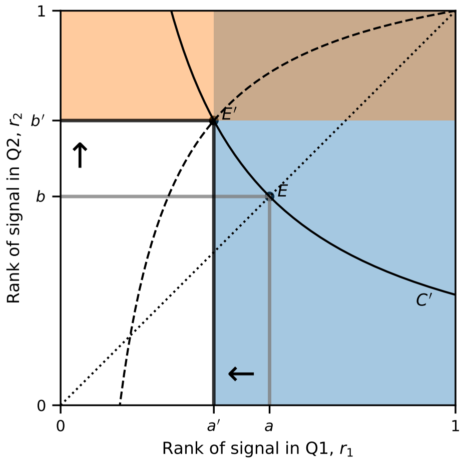


Figure 3: Optimal admission policy with a binding relative-size constraint

Note: The figure shows the effect of imposing a maximum on the share admitted through Q2. The restriction is illustrated by the dashed line. The constrained optimum is E', with accompanying cutoffs a' and b'.

Constraining holistic admissions Before 2012 programs faced a relative-size constraint on Q2. Figure 3 illustrates what happens when the relative size of holistic admissions is capped in the simple model with inelastic applications and equally informative signals. The dashed line traces all cutoffs (a,b) where admissions through Q2 are restricted to a fixed share of total admissions. All pairs above this line are feasible in the sense that the share of holistic admissions does not exceed the cap. The optimal admission policy is where the outer envelope of the equal-marginal-completion locus and the dashed line intersects the marginal cost function, at E' in the figure.

If programs are constrained in setting the size of holistic admissions, then the new cutoffs (a',b') satisfy $b' > b$ and $a' < a$. If the expected completion rate increases in both r_1 and r_2, the marginal Q2 admit then outperforms the marginal Q1 admit. We confront this prediction with the data in Section 6.4, where we study the reform that relaxed a binding 10 percent cap on the relative size of Q2 admissions.

3.2 Program admissions with elastic applications

So far we have taken the pool of applicants as fixed. In practice, application behavior may respond to the cutoffs, affecting both the composition and the size of the Q2 applicant pool in equilibrium.

We assume that applicants apply to Q2 if the expected utility of doing so exceeds the application costs. Normalizing the utility of admission to 1, an applicant's expected utility equals her probability of admission through Q2 which gives the following decision rule:

$$\Pr(r_1 < \hat{a} \wedge r_2 \geq \hat{b} \mid y^1, I) = F_1(\hat{a} \mid y^1)[1 - F_2(\hat{b} \mid y^1, I)] > AC(y^1, I), \tag{3}$$

where $\hat{a}$ and $\hat{b}$ are the applicants' expectations of the Q1 and Q2 cutoffs, and $AC(y^1, I)$ is an application cost that may depend on applicant quality and the screening instruments I.[9]

Both the expected cutoffs and the screening technology affect sorting into the Q2 application pool. Applicants respond to admission probabilities: if the Q1 cutoff falls (higher admission probability in Q1), fewer students find it worthwhile to incur the cost of applying to Q2; if the Q2 cutoff falls, applying to Q2 becomes more attractive. Equation (3) implies that, with positive application costs, the probability of applying to Q2 is hump-shaped in quality, with very high- and very low-quality applicants less likely to apply.

The screening technology I enters (3) in two distinct ways. First, it affects the precision and possible bias of r_2 through F_2 and thus the probability of admission. Second, the assessment instruments can also affect application costs. Some instruments (e.g. interviews or tests) require more time and effort than others (e.g. using specific grades or CVs), and these costs may correlate with applicant quality, generating additional selection into Q2.

Endogenous application behavior rules out a simple closed-form solution of the general model, so we solve the model numerically in Appendix A. The results show that if applicants react strategically to cutoffs, programs can no longer reason solely at the margin. Endogeneity of applications creates two opposing forces.

First, inframarginal benefits can compensate for marginal losses and push the program to lower the bar in Q2. Starting from a situation in which marginal completion rates in the two quotas are equal, slightly lowering the Q2 cutoff b makes a Q2 application more attractive and encourages more students to apply. Some additional applicants may have quality well above the new cutoff, so their admission raises inframarginal completion rates. Even if the marginal Q2 admit has a lower expected completion rate than the marginal Q1 admit, these inframarginal gains can offset the loss at the margin.

Second, screening costs may cause the program to increase the bar in Q2. Because the program incurs screening costs on the entire pool of Q2 applicants, it has an incentive to limit the size of this pool. Increasing b discourages applicants at the margin of

[9]The factorization in (3) uses conditional independence of signals given quality. This is not needed for the edge cases we emphasize below.

entering Q2, keeping screening costs smaller.

How these inframarginal benefits and screening costs net out depends on the joint distribution of quality and signals and cannot be signed a priori. In numerical versions of the model with elastic applications, screening costs tend to push toward marginal Q2 admits outperforming marginal Q1 admits.[10] Thus a positive completion gap between Q2 and Q1 is naturally interpreted as evidence that application behavior is elastic and screening costs matter.

Marginal outcome gaps can also arise when programs value other characteristics of applicants, such as gender or race (e.g., Bhattacharya, Kanaya, and Stevens, 2017). In that case, programs trade off completion against other attributes, creating a wedge between marginal completion rates across quotas. In the Danish context, several features make this interpretation less compelling: institutional rules emphasize academic criteria, funding is explicitly tied to study performance, the reform evidence below shows that lifting relative-size constraints leads programs to close admission gaps, and the sign of any gap would depend on how valued attributes correlate with potential completion (with negative gaps if preferred groups have weaker academic preparation). The characterization of marginal applicants in Section 6.5 is also hard to reconcile with systematic non-academic objectives.

To summarize, the model provides testable predictions for completion gaps among marginally admitted applicants: (i) with inelastic applications, programs equate marginal completion rates across quotas; (ii) when Q2 is constrained, marginal Q2 admits outperform marginal Q1 admits; and (iii) in our baseline model with elastic applications and screening costs, a positive Q2–Q1 completion gap is indicative of elastic applications and binding screening costs. The model assumes that programs care only about outcomes given admission, reflecting the Danish compensation scheme, so program choices need not internalize system-wide completion.

3.3 Sorting and screening

The benefits of holistic admissions potentially arise from two distinct channels: sorting and screening. To illustrate this, consider admitting the first marginal holistic applicant. This substitutes an applicant who chose holistic admissions for an applicant from the regular application pool. This is beneficial if there is positive sorting into Q2. Holistic admissions may also improve completion by screening applicants on additional criteria

[10] In Appendix A we also introduce correlation between application costs and applicant quality. If application costs tend to be smaller for high-quality applicants, programs can optimally lower standards in Q2.

beyond GPA.

Differences between admission regimes that use alternative criteria can therefore arise because of selection into application and because other evaluative criteria admit different applicants conditional on selection. The relative importance of these channels informs the design of admissions. If sorting dominates, imposing costs on applicants is more important than exploiting additional information; if screening dominates, the criteria provide useful information on applicants' completion probabilities.

Sorting and screening can be made precise at the GPA margin, $r_1 = a$, by considering the outcome difference between holistic applicants who would be admitted based on their subjective program ranking ($A_2 = 1\{r_2 \geq b\}$) and regular applicants admitted based on GPA ($A_1 = 1\{r_1 \geq a\}$):

$$E[y^1 \mid A_2 = 1, Q2 = 1, r_1 = a] - E[y^1 \mid A_1 = 1, Q2 = 0, r_1 = a],$$

where the first term is the average y^1 for Q2 applicants admitted through holistic admissions and the second term is the average y^1 for marginally admitted GPA-based applicants who did not apply to Q2.

The performance gap at the GPA margin can be decomposed into sorting and screening components:

$$\begin{aligned} E[y^1 \mid A_2 = 1, Q2 = 1, r_1 = a] - E[y^1 \mid A_1 = 1, Q2 = 0, r_1 = a] = \\ \underbrace{E[y^1 \mid A_1 = 1, Q2 = 1, r_1 = a] - E[y^1 \mid A_1 = 1, Q2 = 0, r_1 = a]}_{\text{Sorting}(r_1)} \\ + \underbrace{E[y^1 \mid A_2 = 1, Q2 = 1, r_1 = a] - E[y^1 \mid A_1 = 1, Q2 = 1, r_1 = a]}_{\text{Screening}(r_1)}. \end{aligned} \quad (4)$$

The first component captures sorting into holistic admissions: differences in performance between applicants who apply to Q2 and those who do not, holding the admission rule (Q1) fixed. The second component captures the incremental benefit of screening Q2 applicants on alternative information rather than GPA alone. We also quantify infra-marginal screening benefits in Section 8.2.

4 Empirical approach

4.1 Recovering potential outcomes at the admission margin

The Deferred Acceptance admission mechanism described in Section 2 admits applicants who are ranked high enough, while applicants with marginally lower rankings are rejected. Programs rank applicants in all quotas for which the applicant is eligible. In Q1, all applicants are ranked according to their GPA. Applicants who also apply for holistic evaluation are ranked based on alternative criteria in Q2. For any program p in year t, the number admitted through Q1 is limited by capacity, and, if the program is oversubscribed, the rank of the last admitted applicant defines the admission cutoff c_{1pt}. Applicants whose Q1 ranking is below c_{1pt} but who applied for holistic evaluation are then considered based on their Q2 ranking. This defines a second cutoff c_{2pt}, the rank of the last admitted applicant in Q2, and applicants above this cutoff are admitted in Q2. Applicants only receive an offer above a cutoff if they are not admitted to a higher-ranked program on their application list.

This setup generates a standard fuzzy regression discontinuity design in which the application cutoff is defined by the application score of the last admitted student (Öckert, 2001, 2010; Kirkeboen, Leuven, and Mogstad, 2016; Heinesen, Hvid, Kirkebøen, Leuven, and Mogstad, Forthcoming). We exploit this design to estimate potential outcomes at the admission margins in equation (1). Because applicants can apply to more than one program, the unit of analysis is the *application* rather than the applicant. We retain all applications and use 2SLS to estimate the expected potential outcomes given admission for the marginal applicant who is admitted to the program if ranked just above the cutoff in a quota but not if ranked just below. This isolates the quota-specific marginal applicants of interest, as illustrated in Figure 2.

To assess the theoretical predictions, our main estimands are completion rates of marginal quota-specific admissions, $E[y^1 \mid r_1 = a, r_2 < b]$ and $E[y^1 \mid r_1 < a, r_2 = b, Q2 = 1]$. These are in levels rather than value-added, i.e. $E[y^1 - y^0 \mid \cdot]$. Following Abadie (2003), we estimate $E[y^1 \mid \cdot]$ by interacting the outcome with the treatment indicator.

The baseline specification of the second stage of our 2SLS estimation is

$$E[A_{ipt}Y_{ipt} \mid A_{ipt}, R_{qipt}, FE_{qpt}] = \delta_q A_{ipt} + B_q(R_{qipt}) + FE_{qpt}, \quad q \in \{1,2\}, \qquad (5)$$

where subscripts highlight that the data are at the application level. We observe whether individual i applied to program p and quota q in year t. The key variable A_{ipt} is a binary indicator for receiving an admission offer for program p in year t; Y_{ipt} is a binary program-completion indicator. Admission and completion are not quota-specific.

To isolate marginal admissions, we instrument A_{ipt} with cutoff crossing $Z_{qipt} \equiv 1\{R_{qipt} \geq 0\}$ in the first stage:[11]

$$E[A_{ipt} \mid Z_{qipt}, R_{qipt}, FE_{qpt}] = \pi_q Z_{qipt} + B_q(R_{qipt}) + FE_{qpt}. \tag{6}$$

We estimate (5) separately for each quota. The quota-specific assignment variable R_{qipt} is defined as the percentile distance of applicant i's application score from the admission cutoff. More specifically, we set R_{qipt} equal to the applicant's rank in quota q minus c_{qpt} (the rank of the last admitted applicant in quota q for program p in year t), divided by the number of Q1 applicants in that program-year. This normalization facilitates comparisons of the slope on the running variables across quotas and across programs. We cluster standard errors at applicant level.[12]

To account for nonlinearities in the running variable, the specification in (5) includes a quadratic spline with a knot at zero, denoted $B_q(R_{qipt})$.[13] Since the application cutoffs are defined at the quota-program-year (qpt) level, we control for program$\times$quota$\times$year fixed effects (FE_{qpt}). While our main results are based on this 2SLS framework, we validate their robustness to changes in the polynomial degree of the spline, reductions in the bandwidth around the admission cutoffs, and the local DA propensity score approach of Abdulkadiroğlu, Angrist, Narita, and Pathak (2022) in Section 6.3.

Programs are not incentivized to internalize outcomes for applicants who are not admitted (i.e. y^0 in potential-outcome notation), so the model does not provide predictions for value added ($y^1 - y^0$) between the marginal Q2 and marginal Q1 admission. However, because higher education is publicly provided in Denmark, we assume that policymakers care about applicants obtaining a college degree on the extensive margin. To quantify potential externalities of program admission, we therefore estimate the effect of admission on completing *any* program (college completion) by changing the dependent variable in (5) to $Y_{college,ipt}$, an indicator for college completion rather than program completion. This recovers an estimate of college-completion value added, $Y^1_{college,ipt} - Y^0_{college,ipt}$. A gap in marginal value added across quotas suggests that program incentives may be misaligned with social preferences.

[11] At the cutoff, for applicants with the same GPA, admission A_{ipt} is determined by lottery. To incorporate this, we define the instrument as $Z_{1ipt} = A_{ipt}$ for Q1 applicants exactly at the cutoff and include a dummy for $r_1 = 0$.

[12] Standard errors on the completion gap across quotas are obtained by stacking the Q1 and Q2 data and clustering on applicants.

[13] We use the generic notation $B_q(R_{qipt})$ and FE_{qpt} throughout, with the understanding that these terms are allowed to vary across specifications.

4.2 Estimating the sorting and screening components

To estimate the sorting and screening components, we recover the outcome difference between holistic applicants who would be admitted based on their subjective program ranking at the GPA margin and regular applicants who are admitted based on GPA:

$$E[y^1 \mid r_1 = a, r_2 \geq b, Q2 = 1] - E[y^1 \mid r_1 = a, Q2 = 0].$$

This gap and its components can be estimated at the GPA admission margin.

In our setup, the first term is identified by Q2 applicants who are always-takers at the GPA cutoff a. We estimate y^1 for always-takers by applying 2SLS to (5) with the dependent variable $Y_{ipt}(1 - Z_{1ipt})A_{ipt}$ and the endogenous variable $(1 - Z_{1ipt})A_{ipt}$.

The second term is the average potential outcome on admission for the marginally admitted applicant who did not apply to Q2. These are regular compliers in the GPA admissions pool without a Q2 application.[14]

Finally, we need to estimate $E[y^1 \mid r_1 = a, Q2 = 1]$, which in the current setup consists of both compliers and always-takers at the GPA admission margin among Q2 applicants. We obtain this term in our 2SLS setup by using $Y_{ipt}Z_{1ipt}A_{ipt}$ as the dependent variable and $Z_{1ipt}A_{ipt}$ as the endogenous variable.

5 Data and descriptive statistics

We use application data for 2010–15 with information on applicants' preference lists, rankings in Q1 and Q2 (if applicable), and program offers. We restrict attention to oversubscribed programs and retain all applications to these programs.

To identify enrollment and completion, we map institution-program-year identifiers in the production data to the Danish education registers (KOTRE). Our primary outcome is program completion: for each application, we record whether a program spell was initiated after August 1 and completed within 5 years. We do not require enrollment in the year of application, as programs control offers rather than enrollment timing.[15] For college completion, we record whether any program spell was initiated and completed within 5 years of applying.

To check balance, we also record gender, age, parental income, high-school grade-

[14] There are no always-takers for this group, as illustrated by the zero admission rate to the right of the cutoff in the first-stage graph in the top panel of Figure 5.

[15] Depending on program length, this definition allows for at least one year of delay. We also record enrollment as beginning a program between August and April, which captures winter-start programs; we replace admission with enrollment in robustness checks which does not change out conclusions.

Table 2: Descriptive statistics for analysis samples

	Main sample (2012-2015)		Additional sample (2010-2011)	
	Full (1)	Q2 (2)	Full (3)	Q2 (4)
Age	21.9	23.0	21.4	22.5
Female	0.65	0.67	0.63	0.64
Immigrant	0.14	0.13	0.13	0.11
SES	0.72	0.72	0.74	0.75
GPA	0.05	-0.26	0.19	-0.09
Apply in Q2	0.48	-	0.43	-
Admitted	0.26	0.25	0.29	0.28
Completes program (conditional on admission)	0.60	0.59	0.62	0.60
Completes college (conditional on admission)	0.74	0.71	0.77	0.74
Applications	485,071	230,319	163,495	68,353
Applicants	218,334	110,551	80,693	36,972

Note: The table shows descriptive statistics for two samples. The unit of observation is an application. The holistic-assessment sample in column 2 is a subset of column 1, and column 4 is a subset of column 3. Depending on timing, parental income and GPA are missing for some immigrants, and we do not observe socioeconomic data for foreign applicants who never move to Denmark. Means are computed excluding missing values.

point average (GPA), and immigrant status. We measure parental income as the parents' income rank it in the national distribution when the child was 13, and rescale high-school GPA to mean zero and unit variance within high-school graduation cohort. Immigrant status follows Statistics Denmark and is coded as not having Denmark as country of origin; this includes non-Danes living in Denmark, descendants in Denmark, and applicants who apply but never move to Denmark. We do not observe socioeconomic information for the latter group.

In our main analysis, we focus on 2012–2015, when there were no restrictions on the share of applicants that programs could admit using holistic assessment. For the reform analysis, we extend the data back to 2010, adding two years.

Table 2 reports descriptive statistics for the main sample (columns 1–2) and the reform sample (columns 3–4). In the main period, about 220 thousand people submit 485 thousand program applications. Among applications with observed gender, 65 percent are from women and 14 percent from applicants with an immigrant background. The average parental-income rank is at the 72nd percentile, reflecting the higher likelihood that high-SES individuals attend tertiary education. Applicants are positively selected on high-school GPA.

Around 48 percent of applications are also evaluated in Q2. Q2 applications are

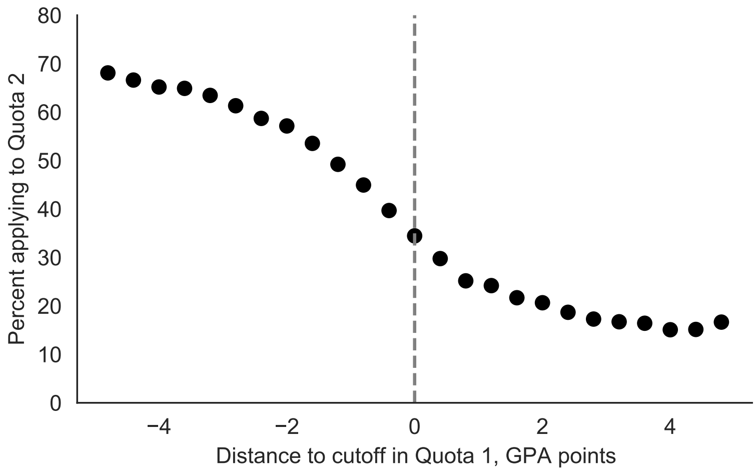


Figure 4: Propensity to apply for Q2 assessment

Note: The figure displays the probability of filing a Q2 application as a function of the distance from the GPA cutoff in a given admission round. The unit on the x-axis is raw GPA points on a scale from -3 to 12. Only applicants assessed in Q1 are included.

more likely to come from women, slightly older applicants, and non-immigrants. They have similar SES but substantially lower standardized GPA, consistent with high-GPA applicants being more likely to gain admission through Q1 and therefore less likely to apply for holistic assessment in Q2.

About 26 percent of applications lead to an offer of admission.[16] Conditional on admission, the program completion rate is around 60 percent, and about 74 percent of admitted applicants complete some college degree within 5 years, so relatively few admitted applicants end up without higher education once they enter an admission round.

Columns 3 and 4 present the same statistics for the sample used to study the lifting of the Q2-size restriction. Applicants are more positively selected in the earlier period in both Q1 and Q2 and are less likely to apply for Q2. This is consistent with applications responding to admission chances when admission through Q2 was less likely, as in our theoretical model.[17]

To further assess the assumptions in the theoretical analysis of endogenous application behavior, Figure 4 plots the propensity to apply for Q2 as a function of the distance to the Q1 cutoff. The propensity declines monotonically from about 70 to about 20 percent and does not drop to zero far above the cutoff. This could point to substan-

[16]While this may sound low, observe that the centralized nature of the admission system ensures that applicants can only get one offer per admission round.

[17]Overall averages need not coincide with the characteristics of applicants at the admission margin. Section 6.5 estimates the characteristics of marginal applicants in the two admission quotas.

Table 3: Bunching and balancing around the admission cutoffs

	Female (1)	Immigrant (2)	Income (3)	GPA (4)	Missing cov. (5)	Apply to Q2 (6)
Holistic (Q2)	-0.007	-0.0	0.0	0.01	0.001	
	(0.007)	(0.005)	(0.004)	(0.01)	(0.004)	
GPA-based (Q1)	0.008	0.004	0.003	0.003	0.003	-0.001
	(0.006)	(0.004)	(0.003)	(0.002)	(0.003)	(0.006)

Note: The table reports validity checks on the regression discontinuity design in Q1 and Q2. In column (5) the dependent variable is a dummy for not observing the applicant in the registers, which indicates that the applicant did not live in Denmark. The balance check is based on the reduced form of (5) with a bandwidth of 20 percentile points on either side. As a robustness test we estimate nonparametric balancing checks and present the results in Appendix Table B1.

tial uncertainty about admissions from the applicants' perspective, and/or application costs being lower for high-quality or high-match applicants—for example because they find essays or interviews less burdensome, or are more confident in clearing the Q2 cutoff. It is smooth around the cutoff, suggesting that applicants at the Q1 cutoff are not inherently different from applicants further away and that the screening–sorting decomposition at the margin is informative more generally. A large fraction of those far below the cutoff apply to Q2, indicating that they perceive admission through Q1 as unlikely.[18] Conditional on having applied, the monotone decline is consistent with the selection implied by (3) and supports the signaling structure in our model.

6 GPA-based vs. holistic admissions

6.1 Validity checks

Before turning to our main results, we test whether applicants around the application cutoff are comparable in terms of observed characteristics that are potential confounders. Balance is required by the RD, which relies on continuity of potential outcomes around the application cutoffs.

We estimate cutoff-crossing "effects" on background characteristics, reported in columns (1)–(6) of Table 3. In the main admission quota, we consider sex, immigrant status, parental income rank, a dummy for missing observables, and whether applicants apply to Q2; for Q2 applicants we also examine GPA. We do not find evidence of im-

[18]The propensity is not hump-shaped as suggested by equation (3) because we do not observe individuals who choose not to apply to the program at all. Including them would likely generate a declining propensity far below the cutoff.

balance and conclude that applicants are similar on both sides of the cutoff.

6.2 Marginal admission rates

We begin by documenting admission rates around the cutoffs and how we estimate the fuzzy RD estimands. There are two sets of potential marginal applicants: those who only apply through Q1 and those who also file a Q2 application. Figure 5 summarizes the three first stages for these two sets.

The top panel shows the first stage for applicants without a Q2 application when assessed on GPA in Q1. For these applicants, the only pathway to admission is through Q1, so the admission rate is zero below the Q1 cutoff. We observe a large discontinuous jump in the admission probability at the cutoff, and above the cutoff admission rates are about 50 percent, reflecting that applicants are often admitted to a higher-priority program.

Applicants with a Q2 application have two pathways to admission and can therefore be on the margin of either quota, depending on their rankings. The corresponding first stages are shown in the middle and right panels of Figure 5. We again observe large discontinuous jumps at the cutoffs, but admission rates are rising below the cutoffs because of positive correlation between Q1 and Q2 rankings, as seen in the joint distribution of the quota-specific running variables in the center panel. The marginal Q1 applicants among Q2 filers have marginal GPA scores but do not clear the Q2 cutoff and are located on the right side of the bottom-left quadrant. Conversely, marginal Q2 applicants have submarginal GPA scores and marginal subjective rankings and are located at the top side of the bottom-left quadrant. In accordance with the mechanism, we do not observe discontinuities in admissions when crossing a cutoff *conditional* on having crossed the other cutoff, i.e. on the border of the top-right quadrant.

The first stages in Figure 5 map directly into the complier populations of interest. In our main analysis, the complier group for the Q1 instrument is a mix of applicants with and without a Q2 application, i.e. a complier-weighted combination of the top two panels. The marginal Q2 applicants are captured in the right panel. Our instrumental-variables approach using quota-specific instruments estimates average effects for these complier groups. Thus, while the joint figure provides intuition, the building blocks of our analysis are the quota-specific one-dimensional fuzzy RD designs. We return to differences between applicants with and without a Q2 application in Section 8.[19]

[19] Quota-specific first stages are shown in Appendix Figure B2, and corresponding reduced forms for educational outcomes in Appendix Figure B3. The discontinuities in Figure B2 are estimated non-parametrically without fixed effects, so they do not correspond directly to our 2SLS estimates, though

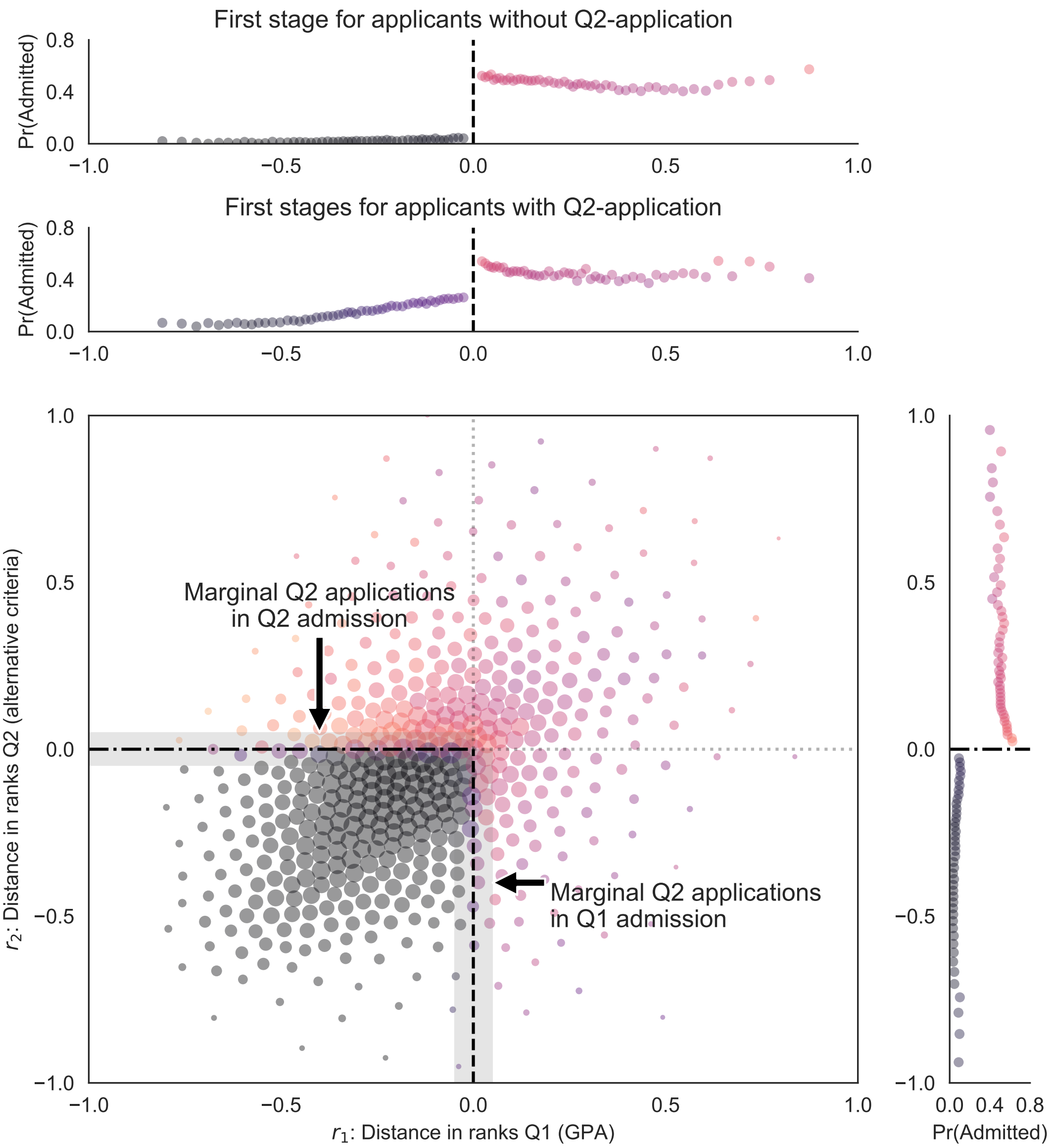


Figure 5: First stages for applicants in GPA-based (Q1) and holistic (Q2) quotas

Note: The figure illustrates the first stages for applicants with and without a Q2 application. The center plot uses K-means with 500 bins; bins are colored by the share admitted to the program. The top figure shows the first stage for Q1 applicants without a Q2 application. The middle and right figures show the first stages for Q1 and Q2, respectively, for applicants with a Q2 application. Observations in the top and right plots are clustered into 100 bins using K-means, excluding the percentile point closest to the cutoff on either side. Appendix Figure B2 presents nonparametric first stages. The dashed lines show the location of marginal applicants in the two quotas; the dotted lines serve as placebo tests for those who should be admitted in the other quota and thus not affected by the quota-specific instrument. Colors correspond to the same values across plots.

Table 4: Potential program and college completion rates and value added – holistic vs. GPA-based admissions

	Program, Y^1	College, Y^1	College, $Y^1 - Y^0$
	(1)	(2)	(3)
Holistic (Q2)	0.587	0.706	0.092
	(0.005)	(0.004)	(0.007)
GPA-based (Q1)	0.577	0.734	0.044
	(0.004)	(0.004)	(0.007)
Q2 vs. Q1	0.011	-0.028	0.048
	(0.006)	(0.006)	(0.01)

Note: The table reports estimated potential completion rates (Y^1) and value added ($Y^1 - Y^0$) with standard errors in parentheses. Standard errors are clustered by program and year in a stacked 2SLS specification. Models are estimated for program and college completion using 2SLS. Results for program value added and program and college Y^0 are reported in Appendix Table **??**.

6.3 Completion rates for marginal applicants

Table 4 presents estimated potential completion rates for marginal applicants at the GPA-based and holistic admission margins based on the 2SLS specification in (5). We focus on three parameters: the average potential program completion rate for marginal applicants (column 1), the marginal college completion rate (column 2), and the value added for college completion (column 3). Differences in value added between the two margins indicate how a marginal change in the relative size of the quotas would affect college completion for marginal admits.

Column (1) shows that the completion rate of the marginal applicant admitted based on holistic criteria (Q2) is 58.7 percent, about 1 percentage point higher than the corresponding rate for marginal GPA-based admits (Q1). We cannot reject equality of these margins. This is consistent with the inelastic-application version of the model, in which programs optimally equalize marginal completion rates, and suggests that any wedges induced by screening costs are small on average.

Column (2) reports marginal college completion rates across quotas. Q2 marginal admits are about 3 percentage points less likely to complete college somewhere than GPA-margin admits, even though their program completion rates are similar. Column (3) shows that this reflects substantially worse outside options for Q2 applicants: The first row implies that admission raises the likelihood that a marginal Q2 applicant completes a college degree by 9.2 percentage points, compared with 4.4 percentage points for the marginal Q1 applicant. College value added at the holistic margin is thus

Appendix Figure B3 shows that the fit is similar.

about 4.8 percentage points higher than at the GPA margin.

Since college completion conditional on admission is similar across quotas, the gap in value added is driven by what happens when marginal applicants are rejected: marginal Q2 applicants are much less likely to complete higher education if the admission in question is denied.[20] This pattern is consistent with Q2 applicants having weaker fallback options—for instance because of lower GPA or different application portfolios—and / or stronger program-specific preferences or match effects that make rejection more costly in terms of eventual college completion.

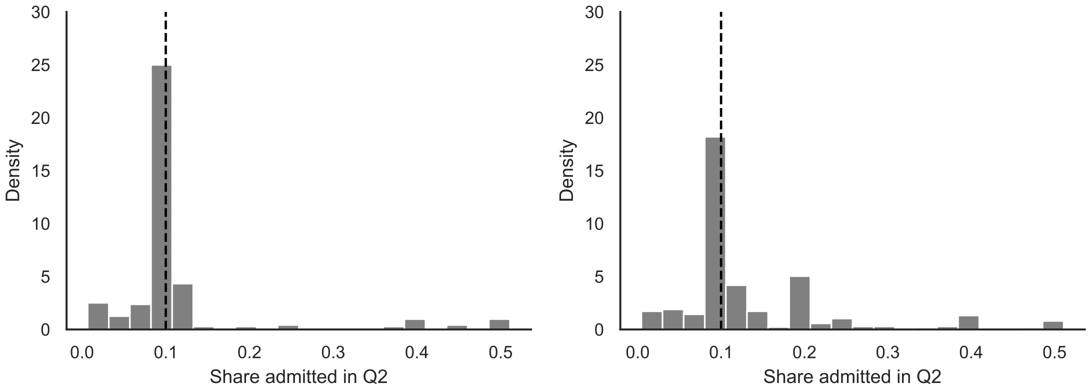
In sum, completion rates of marginal applicants are very similar in Q1 and Q2, suggesting that the simple model with inelastic applications is a good first-order description of programs' admission behavior. The value added estimates indicate that holistic admissions attract applicants with strong program-specific preferences and match effects. The higher value added at the holistic margin suggests that individual programs do not fully internalize the outcomes of rejected applicants, and that overall college completion could be improved by increasing the relative size of holistic admissions in selective programs with small Q2 quotas.

We perform extensive robustness and specification checks in the appendix. Appendix Figure B3 shows that our 2SLS specification with a second-order polynomial and program$\times$quota$\times$year fixed effects captures the nonparametric first stages well. Appendix Table B2 presents nonparametric fuzzy RD estimates that match our main results. Appendix Table B9 documents robustness to bandwidth and flexibility of the running variable. Finally, Appendix Table B3 presents an investigation of possible composition effects which can occur if programs contribute with different complier shares in Q1 and Q2. We find that our results are not sensitive to the reweighing of complier shares.

6.4 Exploiting changes in quota size constraints

The results above show that programs approximately equalize completion rates at the margin in a regime where they can freely choose quota sizes. Before 2012, however, university programs could not admit more than 10 percent of students using holistic evaluations. The framework in Section 3 predicts that binding constraints should generate completion gaps across quotas and that lifting the constraint should allow constrained programs to close such gaps. We test this prediction by exploiting the regulatory change that relaxed the cap on holistic admissions.

[20] For completeness, Appendix Table B9 reports Y^0, Y^1, and value added for both program and college completion.



(a) 2010–2011 (b) 2012–2015

Figure 6: Share of applicants admitted in Q2, academic programs

Share of admitted applicants using holistic evaluation at the program-year level. The dashed line indicates the 10 percent ceiling on Q2 shares, which was lifted in 2012. Programs with Q2 shares above 80 percent are omitted. For comparability, the panels use the same range and number of bins.

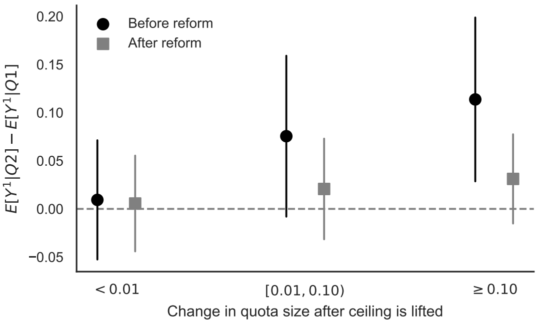
Figure 6a shows that the constraint was binding for a substantial group of academic programs before 2012, with clear bunching around a 10 percent Q2 admission share. After the reform, bunching around 10 percent declines and the mass of programs with Q2 shares above 10 percent rises (Figure 6b). Appendix Figures B4a and B4b show no similar change for non-academic programs, where the 10 percent limit never applied, supporting the interpretation that shifts in Q2 usage are driven by the reform.[21]

We now include the pre-reform years 2010 and 2011 and estimate, for each year, the completion gap between Q2 and Q1 for academic programs. Appendix Figure B5 shows that the gap diminishes somewhat after the reform, but changes are small and imprecisely estimated.[22] This is not surprising: many programs did not increase Q2 usage after 2012, suggesting that they were not initially constrained. Conversely, programs that did expand Q2 usage are natural candidates for having been constrained. Motivated by this, we split programs by the increase in Q2 usage from 2011 to the post-reform period and estimate quota gaps within these groups, reported in Figure 7.

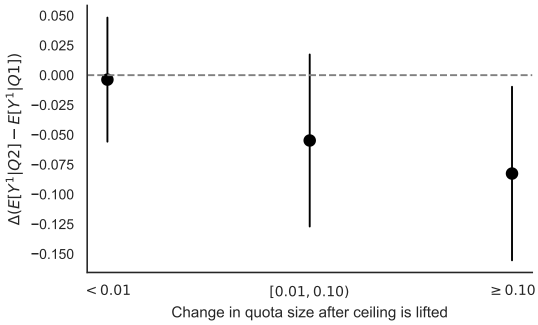
Figure 7a shows large pre-reform differences in the program completion gap across groups. Gaps are generally positive, but programs that later increase their Q2 intake by more than 10 percentage points exhibit pre-reform gaps of more than 10 percentage

[21] Some mass to the right of the 10 percent line pre-reform is due to small programs that cannot satisfy the cap exactly because of the integer nature of admissions. We also see some clustering around 10 percent for non-academic programs, likely reflecting rules-of-thumb in quota setting.

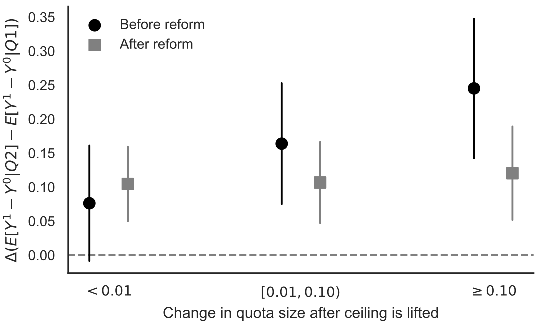
[22] Pooling across years, Appendix Table B4 shows that the sign of the change is as predicted but statistically insignificant.



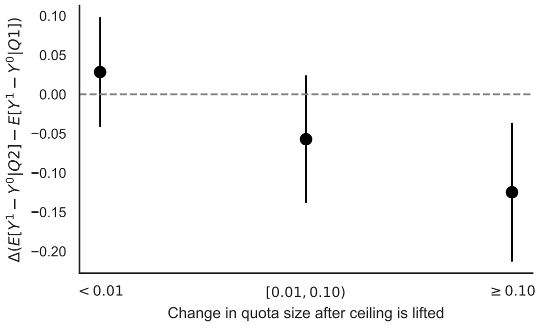
(a) Program completion gap



(b) Change in program completion gap



(c) College value added gap



(d) Change in college value added gap

Figure 7: Completion gap by intensity of constraint

Note: The figure presents across-quota gaps before and after the reform for academic programs, interacting all endogenous variables and instruments with indicators for the change in Q2 admissions relative to Q1 for each program. In panels (a) and (b) the dependent variable is program completion multiplied by the admission indicator, which recovers Y^1. In panels (c) and (d) the dependent variable is college completion, which recovers a LATE on the extensive margin of completing college. Standard errors are clustered at the program level; lines indicate 95 percent confidence intervals. Appendix Figures B6 and B7 report corresponding results for levels of potential outcomes.

points. After the reform, the gap is essentially unchanged for programs that keep their Q2 share constant whereas it falls for programs that expand Q2. For the group with the largest increase in Q2 intake, the completion gap declines by almost 8 percentage points (Figure 7b). This pattern is consistent with constrained programs re-optimizing once the cap is lifted. For these programs we cannot reject equalization of marginal completion rates after the reform.

Panels (c) and (d) repeat the analysis for college value added. Programs that expand Q2 have a large initial gap of over 25 percentage points, which falls by about 10 percentage points after the reform. However, the value-added gap remains positive at around 10 percentage points across programs, again suggesting that programs do not internalize applicants' fallback options when setting admissions. Appendix Figure B7 decomposes the college value-added gap into differences in expected college completion if admitted and if not admitted. The decline in the gap is largely driven by a fall in college Y^1, while the outside option Y^0 remains essentially unchanged. This suggests that programs that increase their Q2 intake draw from a pool with progressively worse program matches until completion rates are equalized across quotas once the cap is removed. Throughout, the marginal non-admitted Q2 applicant has a lower chance of obtaining any higher education than the marginal Q1 applicant, which explains the persistently higher value added for Q2 in Figure 7c.

To summarize, the reform evidence reinforces the conclusion that the theoretical setup in Section 3 provides a good description of program behavior: when the constraint is relaxed, previously constrained programs move toward equalizing marginal completion rates. At the same time, the value-added estimates indicate that holistic admissions systematically attract applicants with strong program-specific preferences and match effects, and that increasing the importance of holistic admissions in selective programs would further raise overall college completion.

6.5 Additional objectives in college admissions?

As discussed in Section 3, programs may have objectives beyond maximizing completion, which could generate gaps in marginal completion rates. Moving a slot from GPA-based to holistic admission exchanges one applicant for another; if programs care about applicant characteristics, a completion gap can reveal preferences over types.

To investigate this, we characterize the composition of marginal applicants at the two margins in our main period. Marginal applicants are not directly identified, but their distributional characteristics are. Following Abadie (2003), we estimate complier-average characteristics by replacing $A_{ipt}Y_{ipt}$ with $A_{ipt}X_{ipt}$ in (5); the second-stage coefficient on A_{ipt} then recovers the complier-average X at the quota-specific cutoff.

Table 5 shows that marginal Q1 applicants have (mechanically) higher GPA than marginal Q2 applicants. They also tend to be younger and come from slightly poorer families; we find no differences in gender or immigrant background.

These patterns help interpret the across-quota completion gap. As noted in Section 3, a positive gap can arise when Q2 applications are elastic and programs trade off inframarginal composition and information gains from holistic screening against screening costs. Gaps could also arise if programs value characteristics other than completion and are willing to accept lower expected marginal completion in order to admit particular groups. The last row of Table 5 shows that the characteristics of the marginal Q1 applicant predict a higher completion rate than those of the marginal Q2 applicant. If programs placed weight on non-academic characteristics that reduce completion, we would expect marginal Q2 applicants to underperform relative to marginal

Table 5: Characteristics of marginal applicants

	GPA-based (Quota 1)		Holistic (Quota 2)	
	est.	se.	est.	se.
Female	0.63	0.00	0.64	0.00
Age	20.65	0.04	23.45	0.06
Immigrant	0.11	0.00	0.12	0.00
Parental income rank	0.75	0.00	0.73	0.00
High school GPA	0.49	0.01	-0.27	0.01
Pr(Program completion|X)	0.64	-	0.55	-

Note: The table shows estimated characteristics of marginal applicants in GPA-based admission (Q1) and holistic admission (Q2). Characteristics are estimated by replacing Y_{ipqt} in (5) with covariates. Standard errors are clustered at the program-year level. We do not observe parental income for 1.2 percent of the sample and exclude these observations from the fourth row. To predict completion based on characteristics we estimate a logit model interacted with field dummies on the subset of admitted applicants and then form predictions for all applicants. We do not report standard errors for predicted completion of compliers, as these do not incorporate uncertainty from the prediction step.

Q1 applicants. This is not the case (Table 4). The evidence is therefore *consistent with* profit maximization together with Q2 screening exploiting information orthogonal to X (e.g., match or non-cognitive traits), rather than systematic preferences for non-academic characteristics that predict lower completion.[23]

7 Program level heterogeneity

The reform analysis revealed sizable cross-program differences in the use of holistic admissions. We now examine heterogeneity in marginal outcomes across programs in the unconstrained reference period. In our framework, a positive Q2–Q1 gap in marginal program completion is consistent with endogenous sorting and screening costs, while heterogeneity in the corresponding college value-added gap indicates where program incentives are misaligned with social objectives. We estimate program-specific gaps using the same quota-specific 2SLS as above and summarize their distribution across programs.

We consider three program-level dimensions: (i) the holistic-admission share of total admits (Q2 share), (ii) program selectivity (proxied by the Q1 cutoff), and (iii) the evaluation instruments used in Q2 (CV, grades, essay, interview, test). These characteristics are, at least in part, chosen by programs and hence endogenous; the estimates below should be read as conditional associations rather than causal effects.[24]

[23]Gandil and Leuven (mimeo) investigate bias in Q2 rankings toward or against minorities.

[24]Heterogeneity by field appears in Appendix Figure B9.

First, we examine how outcomes vary with programs' reliance on holistic admissions. Extensive use of Q2 suggests perceived gains from improved screening and sorting, but at the margin screening costs may eventually prevent programs from expanding Q2 and equalizing completion rates across admission margins. Figure 8a shows marginal completion-rate differences by Q2 share. Most programs display no significant gap in marginal program completion between quotas, but programs with high Q2 intake exhibit a roughly 3 percentage-point gap, suggesting that screening costs become more important as holistic admissions expand.

Mirroring the aggregate results, marginal college-completion rates are lower for Q2 admits regardless of Q2 usage. By contrast, marginal value added varies systematically (Figure 8a, right panel). Programs with low Q2 shares have a value-added advantage of about 12 percentage points, but this gap shrinks to an imprecisely estimated 2 percentage points in programs that rely heavily on holistic admissions. In other words, the programs that would generate the largest social gains from expanding holistic admissions are those currently using this channel the least.[25]

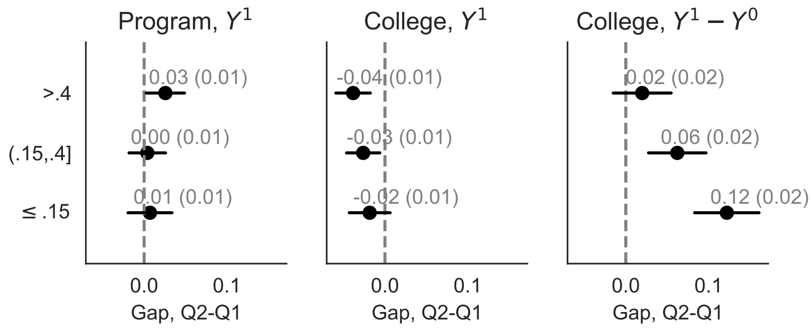
Second, we consider program selectivity as measured by the GPA cutoff in Q1 in the previous year. For a given applicant, higher selectivity in Q1 raises the expected benefit of filing a Q2 application. If screening costs are non-trivial, programs may discourage Q2 applications by limiting admission prospects through Q2. The left-hand panel of Figure 8b reports estimates of the program-completion gap by selectivity. We find the low and moderately selective programs exhibit larger completion gaps, suggesting the presence of screening costs. The right figure in panel b shows suggestive evidence that value-added is larger in more selective programs. In other words, the most selective programs would contribute more to overall degree completion by moving slots from Q1 to Q2.[26]

We find small gaps in all groups and little evidence of systematic patterns. We do not find systematic gaps in college completion rates or value-added either.

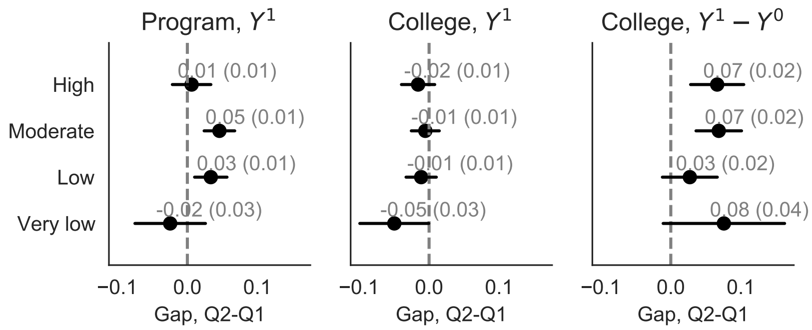
Third, we investigate how patterns differ by holistic evaluation criteria. We expect screening costs and thus marginal completion gaps to vary across criteria. For example, we do not expect interviews as a screening technology to exhibit economies of scale, so programs using interviews have a strong incentive to deter low-quality applicants. By

[25]While we cannot reject the null of no differences across these broad groups (Table B6), 2SLS estimates using the continuous Q2 share yield interaction coefficients of 0.080 (0.013) for the gap in Y^1 and -0.014 (0.008) for college $Y^1 - Y^0$ (standard errors in parentheses).

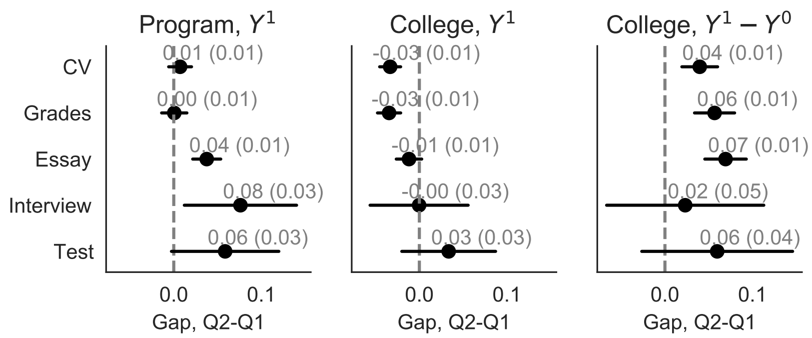
[26]Note that while the gap in value-added for very low selectivity programs is large, the confidence intervals are wide. In Appendix Table B11 we find that with program specific bandwidths and polynomials, the gap in college value-added is monotonically increasing in selectivity.



(a) By importance of holistic admissions



(b) By selectivity (GPA cutoff in previous year)



(c) By evaluation criteria

Figure 8: Difference in completion rates and value added, holistic minus GPA, by program characteristics

Note: The figures report results for different subsets of programs. The leftmost panels show differences in marginal *program* completion rates between holistic (Q2) and GPA-based (Q1) admissions. The middle panels show differences in *college* completion rates. The rightmost panels show differences in college value added. Parameter estimates are shown in gray with standard errors in parentheses. Standard errors are clustered at the program-year level. In Figure 8a the importance of holistic admissions is measured by the share of admitted applicants who enter through Q2. In Figure 8b selectivity is coded as: Very low (cutoff below 4), Low (cutoff below 7), Moderate (cutoff below 10), High (cutoff at least 10), using cutoffs from the previous year. In Figure 8c programs are included if they use a given criterion; programs often use multiple criteria, so the underlying sets overlap. Appendix Figure B8 presents results for all combinations of criteria. Appendix Tables B6, B7, and B8 present formal tests of differences across program categories.

contrast, reviewing grades in specific subjects is likely cheaper to scale. We repeat the analysis conditioning on use of each criterion and present the results in Figure 8c. Gaps in marginal program completion are large in programs using interviews (8 percentage points) and tests (6 percentage points). These gaps are consistent with high screening costs. While tests might in principle scale better than interviews, the positive gap suggests that this is not so in practice; moreover, tests are often used in combination with interviews, making it difficult to disentangle their separate contributions.[27] The smaller but positive gap for programs using essays (4 percentage points) and the absence of gaps for programs using CVs or grades suggest that these latter criteria impose lower marginal screening costs than interviews and tests.

We do not observe clear heterogeneity in marginal college completion rates or college value added by choice of criteria. All criteria are associated with positive value-added gaps ranging from about 4 to 7 percentage points, suggesting that, regardless of the specific evaluation method, holistic admissions tend to identify applicants with strong program-specific preferences or match effects who are less likely to complete college if rejected. We perform extensive robustness checks in terms of the specification of the RDD and present the results in Appendix Tables B10, B11 and B12.

8 Sorting and screening

8.1 Marginal decomposition

Table 6 reports the sorting and screening components in the decomposition of the completion gap between Q2 and the other applicants at the GPA admission margin. We find clear evidence of positive sorting: applicants who apply to the holistic assessment have higher potential completion rates than regular applicants with similar GPA. The point estimate in the pooled sample is about 3 percentage points. This is natural if Q2 entails higher application costs that induce self-selection. By contrast, the screening component is small and statistically indistinguishable from zero, implying that, at the GPA margin, the additional Q2 information does little to improve completion predictions beyond GPA.

While the marginal decomposition shows that sorting is the dominant channel through which holistic admissions improve outcomes, these averages may mask important het-

[27]Combinations of criteria are shown in Appendix Figure B1. For the subset of programs using only tests, we cannot reject that the program-completion gap is zero, though the estimate is imprecise (Appendix Figure B8). We cannot generally reject the null of no differences across assessment criteria; Table B8 reports formal tests.

Table 6: Sorting and screening decomposition for marginal applicants

	Sorting (1)	Screening (2)
All programs	0.033 (0.007)	0.001 (0.008)
Q2 size		
- High	0.034 (0.013)	0.020 (0.014)
- Middle	0.021 (0.012)	0.027 (0.014)
- Low	0.041 (0.010)	-0.062 (0.015)
Selectivity		
- High	0.026 (0.015)	-0.009 (0.021)
- Moderate	0.070 (0.011)	0.022 (0.013)
- Low	0.036 (0.012)	0.023 (0.014)
- Very low	-0.003 (0.027)	0.012 (0.035)
Q2 Criteria		
- CV	0.027 (0.007)	0.000 (0.008)
- Grades	0.027 (0.007)	-0.001 (0.009)
- Essay	0.015 (0.009)	0.025 (0.011)
- Interview	0.032 (0.047)	0.042 (0.050)
- Test	0.137 (0.051)	0.033 (0.054)

Note: Decomposition estimates of the screening and sorting decomposition in equation (4). Sorting is estimated as the difference in the program completion rate of marginal admissions at the GPA margin with and without a Q2 application. Screening is estimated as the difference in the program completion rate of Q2 applicants at the GPA admission cutoff who are admitted based on the subjective assessment compared to all marginal admissions.

erogeneity. Our earlier analysis of completion gaps already documented meaningful variation across program characteristics. To understand how the relative importance of sorting and screening varies between programs, we again consider the extent of Q2 usage, program selectivity, and Q2 evaluation criteria. This helps explain why some programs make greater use of holistic admissions and whether the limited screening benefits we observe on average reflect universal limits or variation in screening capabilities.

Table 6 reports how the sorting and screening components vary with programs' reliance on holistic admissions. Sorting gains tend to be positive for all groups, but screening looks very different across them. Programs that make moderate or extensive use of Q2 show modest sorting benefits and positive screening effects. When a large share of applicants is admitted through Q2, there is mechanically less scope for additional positive selection into the Q2 pool, but these programs appear to extract some predictive power from the additional information. For programs that make very limited use of Q2, we observe strong positive sorting and a large negative screening component: they attract strong applicants through Q2 but then perform poorly at distinguishing among them at the admission margin. These patterns are consistent with Q2 usage reflecting relative advantages in screening versus sorting: programs that have developed effective screening capabilities tend to use Q2 more intensively, while those that mainly benefit from sorting but struggle with screening rely on Q2 more sparingly.

The decomposition by program selectivity shows that holistic admissions generate positive sorting at all selectivity levels. We find no strong evidence of either large benefits or large losses from additional screening: screening estimates are small and imprecise. For the very least selective programs, both sorting and screening estimates are close to zero, with wide confidence intervals. The universal presence of positive sorting—even in highly selective programs—suggests that the costs of holistic applications help identify motivated and well-matched students even among high-GPA applicants.

We also observe strong heterogeneity in sorting and screening across evaluation criteria in Table 6. Programs using tests exhibit especially strong sorting effects, roughly five times of those for programs relying on CVs, grades, or essays, consistent with tests imposing higher application costs. For these same programs, the point estimates for screening are positive but very imprecise; we cannot reject zero effects. Programs using CVs, grades have small and statistically insignificant screening components, and only essays stand out with positive screening. The criteria that appear most effective at inducing positive sorting through high application costs are therefore not clearly more effective at screening, though the imprecision of these estimates and the endogenous choice of criteria warrant caution.[28]

Taken together, the decompositions indicate that the benefits of holistic admissions at the admission margin arise primarily through advantageous self-selection: higher-potential students are more likely to apply through Q2. The additional information used in holistic screening provides, at best, modest improvements beyond GPA, with meaningful screening gains concentrated in programs that already use Q2 more intensively.

We assess the robustness of the decomposition to bandwidth choice and functional-form assumptions in the appendix. Table B13 shows robustness of the aggregate sorting estimate, while Appendix Figures B14, B15, and B16 report robustness by Q2 importance, selectivity, and criteria. Appendix Figure B11 presents decompositions by field.

8.2 Inframarginal considerations

The decomposition in Section 8 compares Q2 and Q1 at the admission margin. This shows what holistic admissions do for applicants at the cutoff. Average completion

[28] Programs choose criteria, and most use multiple criteria in combination. Appendix Figure B10 reports estimates by all criteria combinations.

among admits, and the effect of policies that change capacity or the use of Q2, are inframarginal objects: they depend on how the rule treats the entire admitted distribution, not only the last seat. To speak to such policies, we extend the screening comparison away from the cutoff.

As before, we separate sorting from screening. Inframarginal sorting asks how the distribution of admitted applicants in (r_1, r_2) changes when programs use Q2. Under Denmark's sequential DA, Q1 seats are allocated first and Q2 seats only matter for applicants who are not already sure to be admitted in Q1. High–GPA applicants are almost guaranteed a Q1 offer and therefore have little reason to apply for Q2; in a pure Q2 regime the same applicants would also apply through Q2. The Q2 applicant pool is thus selected toward lower r_1 types, especially away from the cutoff, and the observed (r_1, r_2) distribution of Q2 admits reflects both colleges' rankings and applicants' endogenous Q2 take-up under the current mechanism. This joint selection is different from the counterfactual of interest—re-ranking a fixed applicant pool on r_2 rather than r_1, holding the number of admits fixed—so we do not quantify inframarginal sorting and focus on screening instead.

Inframarginal screening is defined for a fixed pool of applicants. It holds the applicant pool constant and compares completion under two ranking rules that admit the same number of students.[29] For a given program and year consider the applicants who are eligible for Q2. The observed rule ranks these applicants by r_2 and admits those with $r_2 \geq b$ into Q2 seats. The counterfactual screening rule would rank the same applicants by r_1 and admit those with $r_1 \geq a^*$, where a^* is chosen so that the number of Q2 admits is unchanged. The difference in average completion between these two rules is the inframarginal screening gain from using r_2 rather than r_1 for Q2 seats in that program-year.

An analogous comparison is defined for Q1. For each program and year, we hold the number of Q1 admits fixed and compare the observed rule, which ranks applicants by r_1, to a counterfactual screening rule that admits the same number of applicants but now ranked by r_2. One of these two program-level comparisons requires predicting Y^1 for applicants who are never admitted under the corresponding rule. In the implementation we therefore choose, program by program, the comparison that remains on the observed support of Y^1.

Column (1) of Table 7 shows that screening gains are modest but larger away from the cutoff than at the margin. At the margin, screening is essentially zero overall, neg-

[29] As elsewhere, the analysis is partial equilibrium: we abstract from changes in applications, effort, or program choice that might arise if admission rules or capacities were altered.

Table 7: Screening away from the margin of admission

	Screening (1)	$\partial E[y^1 \mid \cdot]/\partial r_1$ (2)	$\partial E[y^1 \mid \cdot]/\partial r_2$ (3)	$\rho(r_1, r_2)$ (4)	Δr_1 (5)	Δr_2 (6)
All programs	0.026 (0.005)	0.11 (0.03)	0.23 (0.02)	0.36	-0.15	0.12
Q2 size						
- High	0.029 (0.006)	-0.00 (0.05)	0.18 (0.03)	0.35	-0.17	0.18
- Middle	0.044 (0.006)	0.06 (0.06)	0.37 (0.05)	0.32	-0.18	0.13
- Low	0.005 (0.005)	0.23 (0.05)	0.36 (0.08)	0.32	-0.12	0.07
Selectivity						
- High	0.030 (0.012)	0.01 (0.12)	0.39 (0.11)	0.32	-0.21	0.16
- Moderate	0.027 (0.006)	0.09 (0.06)	0.25 (0.06)	0.33	-0.17	0.12
- Low	0.025 (0.005)	0.19 (0.04)	0.26 (0.03)	0.44	-0.13	0.12
- Very low	0.017 (0.009)	-0.01 (0.07)	0.17 (0.05)	0.37	-0.12	0.09
Q2 Criteria						
- CV	0.026 (0.004)	0.11 (0.03)	0.23 (0.02)	0.37	-0.15	0.13
- Grades	0.022 (0.004)	0.15 (0.03)	0.27 (0.03)	0.40	-0.14	0.11
- Essay	0.041 (0.005)	0.12 (0.04)	0.22 (0.03)	0.24	-0.19	0.16
- Interview	0.067 (0.026)	-0.23 (0.34)	0.28 (0.17)	0.11	-0.26	0.18
- Test	0.062 (0.036)	0.03 (0.50)	0.37 (0.17)	0.01	-0.28	0.17

Note: Column (1) reports inframarginal screening gains from using the holistic rank r_2 instead of the GPA rank r_1 to allocate a fixed number of seats within program×year cells; values are percentage-point differences in completion probabilities. Columns (2) and (3) report estimated slopes of completion in r_1 and r_2, $\partial E[y^1 \mid \cdot]/\partial r_k$, averaged across cells. Column (4) reports the rank correlation $\rho(r_1, r_2)$ between the two signals. Columns (5) and (6) report changes in mean ranks among admits, Δr_1 and Δr_2, when moving from r_1-based to r_2-based selection (negative Δr_1 and positive Δr_2 indicate that selection shifts toward applicants with lower r_1 and higher r_2). Entries are averages across program×year cells in the indicated groups; standard errors are in parentheses.

ative where Q2 slots are scarce, and positive where Q2 is used more. Inframarginally, average screening gains are about 2 percentage points: close to zero in programs that rarely use Q2 and larger in programs where Q2 plays a bigger role. By selectivity, gains are modest and positive across the board. Across Q2 criteria, gains are larger for essays, interviews, and tests, and smaller for CV and grades; the interview and test estimates are imprecise.

The remaining columns help explain these patterns. Inframarginal screening depends on two ingredients. One is predictive power: the slopes of completion in r_1 and r_2, $\partial E[y^1 \mid \cdot]/\partial r_q$. The other is composition: how much average r_1 and r_2 among admits move when we switch from r_1 to r_2 ($\Delta r_1, \Delta r_2$). The rank correlation between r_1 and r_2 links the two. On average, the r_1–r_2 rank correlation is moderate (0.36), somewhat lower in more selective programs, and especially low when programs use essays, interviews, or tests. When we select on r_2 instead of r_1, average r_1 among admits falls and average r_2 rises ($\Delta r_1 < 0$, $\Delta r_2 > 0$). The r_2 slope is about twice the r_1 slope (0.23

vs. 0.11), so r_2 is clearly more predictive, but the moderate rank correlation means that composition shifts dampen the gains from this extra predictive power. Where r_2 is steep and $\rho(r_1, r_2)$ is low (tests, interviews, essays, and programs with moderate–high Q2 use), screening gains are larger. When Q2 is scarce, marginal screening is weak or negative and inframarginal screening is very small (about 0.5 pp).

The upshot is that predictive power alone is not a good guide to screening gains. Even when r_2 predicts completion better than r_1, switching to r_2 reshuffles who is admitted in ways that can hide or exaggerate these gains. Together with the near-zero effects at the margin, the modest inframarginal gains concentrated where Q2 is used at scale suggest that the main impact of holistic admissions is to change *who* gets admitted. Screening adds, at best, a small improvement in completion.

9 Conclusion

In this paper, we provide, to our knowledge, the first comprehensive analysis of college admissions in a centralized deferred-acceptance system where programs can choose between parallel screening technologies. We study a setting in which Danish bachelor programs admit to the same program through a GPA-based track and a holistic track embedded in a nationwide student-proposing deferred-acceptance mechanism. Within this framework, we develop and test a model of program behavior, recover potential completion rates of marginal applicants at each admission margin, and decompose the gains from holistic admissions into sorting and screening components.

Our results are consistent with programs behaving broadly as if they were optimizing completion outcomes for their own students. In the unconstrained regime, marginal completion rates are very similar across GPA-based and holistic quotas, in line with the model's prediction that optimal programs equalize marginal completion probabilities across tracks. Exploiting the reform that lifted a binding cap on holistic quota sizes, we find that previously constrained programs had substantially higher marginal completion rates in holistic admissions than in GPA-based admissions before the reform, and that these gaps fell once the constraint was relaxed. For these programs we cannot reject that marginal completion rates are equalized across quotas after the reform, consistent with re-optimization toward the first-order condition.

A central insight from our analysis is that sorting is an important driver of the gains from holistic admissions, and screening benefits appear to be modest. Higher-potential students, as measured by subsequent completion, are more likely to apply through the holistic track, and while the additional information used in holistic evaluation adds predictive power beyond GPA, its impact on marginal and inframarginal completion is attenuated by compositional changes. This pattern appears robust across program characteristics, with particularly strong sorting benefits in programs that make little use of holistic evaluations and in programs that rely on high-cost evaluation criteria such as interviews and tests. Away from the cutoff, we find small but positive screening gains, concentrated in programs that use holistic admissions at scale and in those that employ more information-intensive criteria.

At the same time, our results reveal a disconnect between program-level and system-wide optimization. While programs equalize marginal completion rates within their own student bodies, marginal applicants rejected from the holistic quota are about 5 percentage points less likely to complete higher education somewhere in the system than their counterparts at the GPA margin, even though completion rates conditional on admission are similar across quotas. Against baseline marginal completion rates of about 0.5–0.6, this corresponds to a sizable difference in college-completion value added, which is even larger—around twelve percentage points—in selective programs with small holistic quotas. From an aggregate perspective, reallocating seats from GPA to holistic admissions in such programs would therefore raise total degree completion, even though these changes leave program-specific completion largely unchanged. Because marginal holistic-track applicants also have weaker academic records and somewhat poorer family backgrounds than marginal GPA-track applicants, under-use of the holistic track represents both an efficiency loss and a distributionally non-neutral misallocation.

The Danish experience shows that DA-based, GPA-priority systems can incorporate richer applicant information via a parallel holistic track. Our results highlight trade-offs between screening, sorting, and application costs, as well as the externalities created by program-level incentives. Taken together, the patterns point to the importance of aligning admission technology with funding incentives; in practice, this may mean recognizing the role of application costs in generating advantageous sorting and the limited—but real—scope for additional screening beyond GPA within centralized assignment systems.

References

ABADIE, A. (2003): "Semiparametric instrumental variable estimation of treatment response models," *Journal of Econometrics*, 113(2), 231–263.

ABDULKADIROĞLU, A., J. D. ANGRIST, Y. NARITA, AND P. PATHAK (2022): "Breaking ties: Regression discontinuity design meets market design," *Econometrica*, 90(1), 117–151.

Abdulkadiroğlu, A., and T. Sönmez (2003): “School choice: A mechanism design approach,” *American economic review*, 93(3), 729–747.

Allensworth, E. M., and K. Clark (2020): “High school GPAs and ACT scores as predictors of college completion: Examining assumptions about consistency across high schools,” *Educational Researcher*, 49(3), 198–211.

Arcidiacono, P., and M. Lovenheim (2016): “Affirmative action and the quality-fit trade-off,” *Journal of Economic Literature*, 54(1), 3–51.

Arcidiacono, P., M. Lovenheim, and M. Zhu (2015): “Affirmative action in undergraduate education,” *Annual Review of Economics*, 7(1), 487–518.

Avery, C., and J. Levin (2010): “Early admissions at selective colleges,” *American Economic Review*, 100(5), 2125–2156.

Avery, C. N., G. Kocks, and P. A. Pathak (2025): “The Algorithm Advantage: Ranked Application Systems Outperform Decentralized and Common Applications in Boston and Beyond,” NBER Working Paper 34207, National Bureau of Economic Research.

Azevedo, E. M., and J. D. Leshno (2016): “A supply and demand framework for two-sided matching markets,” *Journal of Political Economy*, 124(5), 1235–1268.

Bastedo, M. (2021): “Holistic admissions as a global phenomenon,” in *Higher education in the next decade*, ed. by H. D. H. Eggins, A. Smolentseva, Global Perspectives on Higher Education, pp. 91–114. Brill.

Beattie, G., J.-W. P. Laliberté, and P. Oreopoulos (2018): “Thrivers and divers: Using non-academic measures to predict college success and failure,” *Economics of Education Review*, 62, 170–182.

Belasco, A. S., K. O. Rosinger, and J. C. Hearn (2015): “The test-optional movement at Americas selective liberal arts colleges: A boon for equity or something else?,” *Educational Evaluation and Policy Analysis*, 37(2), 206–223.

Bennett, C. T. (2022): “Untested admissions: Examining changes in application behaviors and student demographics under test-optional policies,” *American Educational Research Journal*, 59(1), 180–216.

Bhattacharya, D., S. Kanaya, and M. Stevens (2017): “Are university admissions academically fair?,” *Review of Economics and Statistics*, 99(3), 449–464.

Bjerre-Nielsen, A., and E. Chrisander (2022): “Voluntary Information Disclosure in Centralized Matching: Efficiency Gains and Strategic Properties,” *arXiv preprint arXiv:2206.15096*.

Bleemer, Z. (2022): “Affirmative action, mismatch, and economic mobility after California’s Proposition 209,” *The Quarterly Journal of Economics*, 137(1), 115–160.

BORGHESAN, E. (2025): "The Heterogeneous Effects of Changing SAT Requirements in Admissions: An Equilibrium Evaluation," Unpublished manuscript.

BURTON, N. W., AND L. RAMIST (2001): "Predicting Success in College: SAT Studies of Classes Graduating since 1980," Research report no. 2001-2, College Entrance Examination Board.

CHADE, H., G. LEWIS, AND L. SMITH (2014): "Student portfolios and the college admissions problem," *Review of Economic Studies*, 81(3), 971–1002.

DYNARSKI, S., A. NURSHATAYEVA, L. C. PAGE, AND J. SCOTT-CLAYTON (2023): "Addressing nonfinancial barriers to college access and success: Evidence and policy implications," in *Handbook of the Economics of Education*, vol. 6, pp. 319–403. Elsevier.

ELLISON, G., AND P. A. PATHAK (2025): "Optimal School System and Curriculum Design: Theory and Evidence," NBER Working Paper 34091, National Bureau of Economic Research.

EPPLE, D., R. ROMANO, AND H. SIEG (2006): "Admission, tuition, and financial aid policies in the market for higher education," *Econometrica*, 74(4), 885–928.

——— (2008): "Diversity and affirmative action in higher education," *Journal of Public Economic Theory*, 10(4), 475–501.

FRIEDRICH, B. U., M. B. HACKMANN, A. KAPOR, S. MORONI, AND A. B. NANDRUP (2024): "Interdependent Values in Matching Markets: Evidence from Medical School Programs in Denmark," NBER Working Paper No. 32325, National Bureau of Economic Research.

FU, C. (2014): "Equilibrium tuition, applications, admissions, and enrollment in the college market," *Journal of Political Economy*, 122(2), 225–281.

GANDIL, M., AND E. LEUVEN (2022): "College Admission as a Screening and Sorting Device," Za discussion paper no. 15557, Institute of Labor Economics (IZA).

——— (mimeo): "Minority bias in holistic college admissions: consequences for equality of access to education," Discussion paper, University of Oslo.

GOHO, J., AND A. BLACKMAN (2006): "The effectiveness of academic admission interviews: an exploratory meta-analysis," *Medical Teacher*, 28(4), 335–340.

HASTINGS, J. S., C. A. NEILSON, AND S. D. ZIMMERMAN (2013): "Are some degrees worth more than others? Evidence from college admission cutoffs in Chile," Discussion paper, National Bureau of Economic Research.

HEINESEN, E., C. HVID, L. J. KIRKEBØEN, E. LEUVEN, AND M. MOGSTAD (Forthcoming): "Instrumental variables with unordered treatments: Theory and evidence from returns to fields of study," *Journal of Labor Economics*.

HURWITZ, M., J. SMITH, S. NIU, AND J. HOWELL (2015): "The Maine question: How is 4-year college enrollment affected by mandatory college entrance exams?," *Educational Evaluation and Policy Analysis*, 37(1), 138–159.

HYMAN, J. (2017): "ACT for all: The effect of mandatory college entrance exams on postsecondary attainment and choice," *Education Finance and Policy*, 12(3), 281–311.

KAMIS, R., J. PAN, AND K. K. SEAH (2023): "Do college admissions criteria matter? Evidence from discretionary vs. grade-based admission policies," *Economics of Education Review*, 92, 102347.

KIRKEBOEN, L. J., E. LEUVEN, AND M. MOGSTAD (2016): "Field of study, earnings, and self-selection," *The Quarterly Journal of Economics*, 131(3), 1057–1111.

KNIGHT, B., AND N. SCHIFF (2022): "Reducing frictions in college admissions: Evidence from the Common Application," *American Economic Journal: Economic Policy*, 14(1), 179–206.

KUNCEL, N. R., R. J. KOCHEVAR, AND D. S. ONES (2014): "A meta-analysis of letters of recommendation in college and graduate admissions: Reasons for hope," *International Journal of Selection and Assessment*, 22(1), 101–107.

LEE, S.-H. (2009): "Jumping the curse: Early contracting with private information in university admissions," *International Economic Review*, 50(1), 1–38.

MURPHY, S. C., D. M. KLIEGER, M. J. BORNEMAN, AND N. R. KUNCEL (2009): "The predictive power of personal statements in admissions: A meta-analysis and cautionary tale," *College and University*, 84(4), 83.

ÖCKERT, B. (2001): "Effects of higher education and the role of admission selection," Ph.D. thesis, Stockholm University, Faculty of Social Sciences, The Swedish Institute for Social Research (SOFI).

——— (2010): "What's the value of an acceptance letter? Using admissions data to estimate the return to college," *Economics of Education Review*, 29(4), 504–516.

OTERO, S., N. BARAHONA, AND C. DOBBIN (2021): "Affirmative Action in Centralized College Admission Systems: Evidence from Brazil," Working paper, Stanford Institute for Economic Policy Research, Unpublished manuscript.

PALLAIS, A. (2015): "Small differences that matter: Mistakes in applying to college," *Journal of Labor Economics*, 33(2), 493–520.

ROTHSTEIN, J. M. (2004): "College performance predictions and the SAT," *Journal of Econometrics*, 121(1-2), 297–317.

SABOE, M., AND S. TERRIZZI (2019): "SAT optional policies: Do they influence graduate quality, selectivity or diversity?," *Economics Letters*, 174, 13–17.

Sacerdote, B., D. O. Staiger, and M. Tine (2025): "How Test Optional Policies in College Admissions Disproportionately Harm High Achieving Applicants from Disadvantaged Backgrounds," NBER Working Paper 33389, National Bureau of Economic Research.

Smith, J., M. Hurwitz, and J. Howell (2015): "Screening mechanisms and student responses in the college market," *Economics of Education Review*, 44, 17–28.

UFM (2020): "Evaluering af optagelsessystemet til de videregaaende uddannelser," Discussion paper, Ministry of Higher Education and Science.

Zwick, R. (2007): "College admission testing," Report, National Association for College Admission Counseling.

A Appendix: Theoretical framework

A.1 Optimal admission without sorting into holistic admissions

When all applicants are considered in Quota 1 and 2 the program is maximizing the following objective function where it is setting quota sizes through the respective admission cutoffs a and b:

$$\begin{aligned}
&\max_{a,b} E(y^1 \mid \text{offer}=1)\Pr(\text{offer}=1) - C(\Pr(\text{offer}=1)) \\
&\quad = \max_{a,b} \int_0^1\int_0^1 E[y^1|r_1,r_2]f(r_1,r_2)dr_2dr_1 - \int_0^a\int_0^b E[y^1|r_1,r_2]f(r_1,r_2)dr_2dr_1 \\
&\qquad\qquad - C(1-\int_0^a\int_0^b f(r_1,r_2)dr_2dr_1),
\end{aligned}$$

where y^1 is the expectation of the completion rate conditional on admittance and r_1 and r_2 are the rankings in Quota1 and 2 respectively with their joint density denoted f.

The first-order conditions are

$$\begin{aligned}
\frac{\partial}{\partial a} &= -\int_0^b E[y^1|r_1,r_2]f(a,r_2)dr_2 + C'\int_0^b f(a,r_2)dr_2 = 0 \\
\frac{\partial}{\partial b} &= -\int_0^a E[y^1 r_1,b)f(r_1,b]dr_1 + C'\int_0^a f(r_1,b)dr_1 = 0
\end{aligned}$$

from which it follows that

$$\frac{\int_0^b E[y^1|r_1=a,r_2]f(a,r_2)dr_2}{\int_0^b f(a,r_2)dr_2} = \frac{\int_0^a E[y^1|r_1,r_2=b]f(r_1,b)dr_1}{\int_0^a f(r_1,b)dr_1} = C'$$

which can also be written as

$$E(y^1 \mid r_1=a, r_2<b) = E(y^1 \mid r_1<a, r_2=b) = C'$$

which shows that the program equalizes completion rates across the two admission margins.

Constrained admissions Adding a relative size constraint that restricts Quota 2 admissions not to exceed a share α of total admissions

$$\alpha\Pr(\text{offer}=1) \geq \Pr(r_1<a, r_2\geq b) \tag{7}$$

gives the following FOCs:

$$
\begin{aligned}
\frac{\partial}{\partial a} &= -\int_0^b E[y^1|r_1 = a, r_2] f(a, r_2) dr_2 + C' \int_0^b f(a, r_2) dr_2 \\
&\quad - \lambda (f_{r_1}(a) - (1-\alpha) \int_0^b f(a, r_2) dr_2) = 0 \\
\frac{\partial}{\partial b} &= -\int_0^a E[y^1|r_1, r_2 = b] f(r_1, b) dr_1 + C' \int_0^a f(r_1, b) dr_1 \\
&\quad + \lambda (1-\alpha) \int_0^a f(r_1, b) dr_1 = 0
\end{aligned}
$$

where λ is the Lagrange multiplier on the constraint (7). These can be rewritten as

$$
\begin{aligned}
E[y^1 \mid r_1 = a, r_2 \leq b] &= C' - \lambda \frac{f_{r_1}(a) - (1-\alpha) \Pr(r_2 < b \mid r_1 = a)}{\Pr(r_2 < b \mid r_1 = a)} \\
E[y^1 \mid r_1 \leq a, r_2 = b] &= C' + \lambda (1-\alpha)
\end{aligned}
$$

If the constraint is not binding $\lambda = 0$ then we are in the case above. If the constraint is binding then $\lambda > 0$ and we see that now the marginal applicants at the holistic admission margin outperform the marginal applicants in the regular GPA-based admissions:

$$
E[y^1 \mid r_1 \leq a, r_2 = b] > E[y^1 \mid r_1 = a, r_2 \leq b]
$$

A.1.1 Optimal admission when not everybody is applying to Quota 2

Individuals now decide whether to apply to the secondary quota ($Q2$), where other criteria are used. Let U_1 be utility if admitted and U_0 if not, and define $\Delta U \equiv U_1 - U_0 > 0$.

Applicants who apply to $Q2$ must submit additional information I at cost $AC(I) > 0$. They apply (and submit I) if the expected benefit of applying exceeds the application cost:

$$
\Pr(r_1 < a,\ r_2 \geq b \mid I)\, \Delta U - AC(I) > 0 \quad \Longleftrightarrow \quad \frac{AC(I)}{\Delta U} < \Pr(r_1 < a,\ r_2 \geq b \mid I).
$$

Hence the share that applies to $Q2$ is a function of the cutoffs (a, b). Let $G(\cdot)$ denote the CDF of $AC(I)/\Delta U$ in the applicant population. Then

$$
P2 \equiv \Pr(Q2 = 1) = E\left[\mathbf{1}\left\{ \frac{AC(I)}{\Delta U} \leq \Pr(r_1 < a,\ r_2 \geq b \mid I) \right\} \right] = E[G(\Pr(r_1 < a,\ r_2 \geq b \mid I))].
$$

If $\Pr(r_1 < a,\ r_2 \geq b \mid I)$ does not vary with I (or is independent of $AC(I)/\Delta U$), this simplifies to

$$P2(a,b) = G(\Pr(r_1 < a,\ r_2 \geq b))\,.$$

With endogenous $Q2$ applications the program's objective is

$$\max_{a,b}\ E(y^1 \mid \text{offer}=1, Q2=1)\Pr(\text{offer}=1 \mid Q2=1)\Pr(Q2=1)$$
$$+E(y^1 \mid \text{offer}=1, Q2=0)\Pr(\text{offer}=1 \mid Q2=0)\Pr(Q2=0) - SC(\Pr(Q2=1)) - C(\Pr(\text{offer}=1)),$$

where $SC(\cdot)$ is the screening cost (increasing in the $Q2$ applicant pool) and $C(\cdot)$ is the offer cost.

When $Q2$ applications are inelastic, the cutoffs equate the expected completion rates of marginal applicants to the marginal admission cost:

$$E(y^1 \mid r_1 = a, Q2=0)\,\omega + E(y^1 \mid r_1 = a, r_2 < b, Q2=1)\,(1-\omega)$$
$$= E(y^1 \mid r_1 < a, r_2 = b, Q2=1) = C', \quad (8)$$

where the first term is the marginal $r_1 = a$ completion rate (mixing $Q2 = 0$ applicants and $Q2 = 1$ applicants with $r_2 < b$), and the second term is the marginal $r_2 = b$ completion rate among $Q2$ applicants with $r_1 < a$.

With elastic $Q2$ applications, two additional forces arise: (i) the *size* of the $Q2$ pool responds to (a,b), and (ii) the *composition* of $Q2$ applicants changes. For $x \in \{a,b\}$,

$$P2_x \equiv \frac{\partial}{\partial x}\Pr(Q2=1) \neq 0, \qquad f2_x \equiv \frac{\partial}{\partial x} f(r_1, r_2 \mid Q2=1) \neq 0.$$

Let $g(r_1, r_2; a, b) = \Pr(Q2 = 1 \mid r_1, r_2, a, b)$ be the $Q2$ application propensity. Then

$$P2(a,b) = \iint g(r_1,r_2;a,b)\, f(r_1,r_2)\, dr_1 dr_2, \qquad f(r_1,r_2 \mid Q2=1) = \frac{g(r_1,r_2;a,b)\, f(r_1,r_2)}{P2(a,b)},$$

and the derivatives satisfy

$$P2_x = \iint \frac{\partial g}{\partial x}(r_1,r_2;a,b)\, f(r_1,r_2)\, dr_1 dr_2,$$
$$f2_x = f(r_1,r_2 \mid Q2=1)\left(\frac{\partial \ln g}{\partial x} - \frac{P2_x}{P2}\right),$$

with $\iint f2_x\, dr_1 dr_2 = 0$. Define $A2 \equiv \{r_1 < a,\ r_2 \geq b\}$, let $C' \equiv C'(\Pr(\text{offer}=1))$ and $SC' \equiv SC'(P2)$, denote f_{r_1} the marginal of r_1, and $f_{r_1|Q2}$, $f_{r_2|Q2}$ the $Q2$-conditional marginals. Define $A2 \equiv \{r_1 < a,\ r_2 \geq b\}$. Let

$$\mathbf{1}_{A2} \equiv \mathbf{1}\{(r_1, r_2) \in A2\} = \mathbf{1}\{r_1 < a,\ r_2 \geq b\},$$
$$\mathbb{E}_{Q2}[h(r_1, r_2)] \equiv \iint h(r_1, r_2)\, f(r_1, r_2 \mid Q2 = 1)\, dr_2\, dr_1.$$

The first-order conditions are

$$\begin{aligned}
0 \;=\; \frac{\partial \mathscr{J}}{\partial a} = & \underbrace{\left[E(y^1 \mid r_1 = a) - C'\right] f_{r_1}(a)}_{\text{GPA boundary (Q1 margin)}} \\
& - \underbrace{\left[E(y^1 \mid r_1 = a, r_2 \geq b, Q2 = 1) - C'\right] \Pr(r_2 \geq b \mid r_1 = a, Q2 = 1)\, f_{r_1|Q2}(a)\, P2}_{\text{Q2 boundary at } r_1 = a} \\
& + \underbrace{P2\, \mathbb{E}_{Q2}\left([y^1 - C']\, \mathbf{1}_{A2} \frac{\partial \ln g}{\partial a} \right)}_{\text{within-Q2 composition (selection slope)}} \;-\; \underbrace{SC'\, P2_a}_{\text{Q2 volume externality}} ,
\end{aligned} \tag{9}$$

$$\begin{aligned}
0 \;=\; \frac{\partial \mathscr{J}}{\partial b} = & \underbrace{-\left[E(y^1 \mid r_1 < a, r_2 = b, Q2 = 1) - C'\right] \Pr(r_1 < a \mid r_2 = b, Q2 = 1)\, f_{r_2|Q2}(b)\, P2}_{\text{Q2 boundary at } r_2 = b} \\
& + \underbrace{P2\, \mathbb{E}_{Q2}\left([y^1 - C']\, \mathbf{1}_{A2} \frac{\partial \ln g}{\partial b} \right)}_{\text{within-Q2 composition (selection slope)}} \;-\; \underbrace{SC'\, P2_b}_{\text{Q2 volume externality}} .
\end{aligned} \tag{10}$$

Consider increasing a (shrinking Quota 1). In (9), the first two lines are boundary substitutions at the GPA cutoff: applicant mass shifted at $r_1 = a$ on the Quota 1 side and at the aligned Q2 boundary, both evaluated relative to C'. The remaining terms are infra-marginal Q2 responses. The composition (intensive-margin) term is governed by the score-slope $\partial \ln g / \partial a$ within $A2$ and is typically negative if a higher a draws in applicants from regions of $A2$ with lower y^1. The volume (extensive-margin) term is the screening-cost effect $-SC'\, P2_a$, which raises costs when $P2_a > 0$.

Tightening Q2 by increasing b is analogous in (10). The first line is the Q2 boundary substitution at $r_2 = b$, relative to C'. The composition term depends on $\partial \ln g / \partial b$ within $A2$ and is typically positive when a higher b mainly deters low-y^1 applicants, improving the pool. The screening-cost term is $-SC'\, P2_b$, which usually reduces screening costs because $P2_b < 0$.

Taken together, elastic applications generate a wedge between the Quota 1 and Quota 2 marginal completion conditions through two channels that are explicit in (9)–(10): a screening-cost component proportional to $P2_x$ and a composition component proportional to $P2$ and the slope of the Q2 application propensity within $A2$. The signs of these terms are empirical, with the typical cases noted above.

A.2 Simulation model with endogenous application behavior

In this section we develop a numerical simulation building on the model in Section A.1.1 with endogenous application behavior and screening costs. The numerical model shares similarities in structure to Chade, Lewis, and Smith (2014) who investigate how different programs compete. In our case there is only one program which fully internalizes applicant behavior and the admissions across quotas. To ease exposition in the model we change notation slightly relative to Section A.1.

A.2.1 The model

The program faces an applicant pool of unit mass with a quality distribution $f(y)$ over $[0,\infty)$. The program has two quotas, $q \in (1,2)$. All applicants apply in Quota 1 but if they want to enter the Quota 2 applicant pool they must incur cost s. This cost is individual and may be correlated with quality y.

Both applicants and the program know f. Students know their own quality but y is unobserved by the program. Instead the program observes a noisy quota-specific signal, σ_q, drawn from a distribution, $G(\sigma_q|y)$. Note that the dependence of the signals on quality, y, implies that the signals σ_1 and σ_2 will be positively correlated.

The program observes signals and sets cutoffs, a and b, such that an applicant is admitted if either $\sigma_1 > a$ or $\sigma_2 > b$, where the latter is conditional on applying to Quota 2 (otherwise σ_2 is not sent). Note that contrary to the theoretical results in this simulation model the cutoffs are set in terms of the cardinal signal values. As such, b does not itself pin down the size of Quota 2 because the size of the Quota 2 pool is allowed to change. We normalize the applicant utility of applying to Quota 2 to one, and an applicant will apply to Quota 2 if the probability of being admitted in Quota 2 outweighs the application costs:

$$(1 - Pr(\sigma_1 > a|y))Pr(\sigma_2 > b|y) > s, \tag{11}$$

where the possible correlation between y and s is left implicit. The tendency to apply to Quota 2 increases in a reflecting that access to the program through the primary admission channel decreases. The tendency to apply to Quota 2 decreases in the Quota 2 cutoff, reflecting the lower probability of admission. Note that the lowest quality and highest quality applicants will never apply to Quota 2 in the presence of application costs. Define $Q2$ as an indicator for applying to Quota 2, i.e. the expected utility being higher than the application costs. Define admissions as $A = \mathbf{1}\left[\sigma_1 > a \vee (\sigma_2 > b \wedge Q2)\right]$.

Programs face the following decision problem:

$$max_{a,b} E[y|A]Pr(A) - \frac{c}{2}Pr(A)^2 - \frac{d}{2}Pr(Q2)^2, \tag{12}$$

where c is the marginal cost of admissions and d is the marginal screening costs. The programs knows the overall quality distribution, f and must make predictions based on the signals received from the applicants and the propensity to apply in Quota 2 given quality. Relative to the model in the main text, this model incorporates endogenous sorting of applicants into Quota 2 and screening costs. The baseline model can be achieved by setting $s = 0$ and $d = 0$.

To illustrate the importance of these two channels for the interpretation of the marginal completion gap we chose parametric forms for the skill distribution f and choose parameters to ensure an interior solution. For these parameters we simulate three scenarios:

1. Applications endogenously select to apply for Quota 2 and programs face no screening costs. Application costs are uniformly distributed at the unit interval and uncorrelated with applicant quality.

2. The same as 1 but now programs endure screening costs of applicants in Quota 2.

3. The same as 2 but with a negative correlation between applicant quality and application costs.

Choice of functional form and parameters For the quality distribution we choose an inverse gamma distribution:

$$f_y(y) = \frac{\beta^\alpha}{\Gamma(\alpha)} y^{-\alpha-1} e^{-\beta/y},$$

where we set $\alpha = 4$ and $\beta = 5$. Let F_y be the associated cumulative distribution function of f_y. We set the marginal admission cost, $c = 3.5$ and the screening cost in scenario 2 and 3 to $d = 0.2$

We assume that the signals follow and exponential distribution, $G(\sigma_q|y) = 1 - e^{\sigma_q/y}$. As noted by Chade, Lewis, and Smith (2014) this distribution has the property that programs almost always reject very low quality applicants and almost always accept very high-quality applicants, i.e. $G(\sigma_q|y) \to 1$ as $y \to 0$ and $G(\sigma_q|y) \to 0$ as $y \to \infty$. The results are not dependent on the choice of exponential distribution and holds for a larger family of signal distributions.

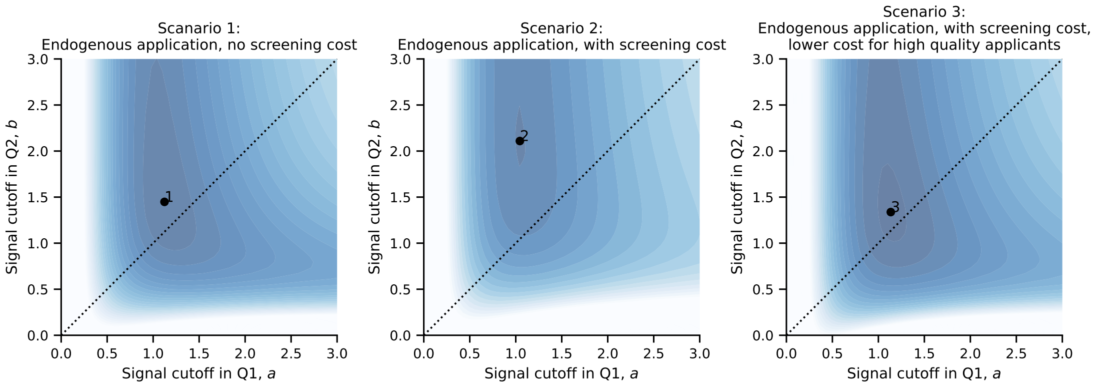


Figure A1: Objective function in cutoff space

Note: The figures show the countures of the objective function in Equation (12) as a function of cutoffs in Quota 1, a, and Quota 2, b. The circles indicate the optimum in each scenario. Negative values of the objective functions are masked with white.

Finally, to model dependence between applicant quality and application costs in scenario 3 we use a Farlie–Gumbel–Morgenstern copula:

$$c(u,v) = 1 + \theta(1-2u)(1-2v)$$

where $\theta \in [-1,1], u = F_s(s)$ and $v = F(y)$, where we set the marginal distribution of s to be uniform on the unit interval such that $u = s$. When we introduce correlation we set $\theta = -1$ which implies a Spearman correlation of $-1/3$.

A.2.2 Simulation results

We begin by presenting contour plots of the objective function in signal space in Figure A1. The optimum in each scenario is indicated by a black circle. In the left-most figure the program faces endogenous Quota 2 application but pays no screening costs. We observe that the programs sets the application cutoff higher in Quota 2 than in Quota 1, thereby inducing positive sorting of applicants into Quota 2 as lower quality applicants are now discouraged from applying. In the center figure we introduce screening costs. While the optimal cutoff in Quota 1 changes little, the cutoff in Quota 2 is much higher, which reflects that the program recognizes that a lower cutoff would force the program to assess more applicants and thus face higher screening cost. In the first scenarios the endogenous selection thus move the program to set higher standards in Quota 2 than in Quota 1. In scenario 3, shown in the figure to the right, we introduce a negative correlation between applicant quality and application costs. The optimal cutoffs are now much more aligned across the two admission quotas. In this case the application cost allows the program to exploit the self selection into Quota 2.

Implication for gaps in quality of marginal applicants Our core analysis abstracts from endogenous sorting into Quota 2 and screening costs which allows us to state first-order conditions in terms of gaps between the quality of marginal applicants across quotas, i.e. the marginal completion gap of compliers, $E[y|\sigma_1 < a, \sigma_2 = b, Q2] - E[y|\sigma_1 = a, (Q2 \wedge \sigma_2 < b) \vee \neg Q2]$.

To assess the importance of the assumptions in the main analysis, we present the gap in quality of marginal applicants as a function of the cutoffs set by the program in Figure A2. The left most figure present the gaps for scenario 1 and 2. The redder the contour the higher the gap, i.e. the better is the marginal Quota 2 applicant relative to the marginal Quota 1 applicant. The dashed line indicates the zero gap and crosses the diagonal only once. This is due to the endogenous selection into Quota 2 application. If programs want to obtain marginal completion rates they thus generally must require different standards in the two quotas (Low standards in Quota 1 must be accompanied by high standards in Quota 2 and vice versa).

The simulations show that the program does not equalize at the margin in optimum in the presence of endogenous application behavior. In the first scenario we observe a negative gap, i.e. Quota 1 outperforms Quota 2 on the margin. The reflects that the program is willing to accept a loss at the margin to induce self-selection into Quota 2. However when we introduce screening cost, the gap flips such that the marginal Quota 2 applicant outperforms the marginal Quota 1 applicant, reflecting that in this particular case, the program takes a marginal loss by having to small Quota 2 to limit the mass of applicants it needs to assess. The third scenario with systemic correlation does not change this conclusion as evidenced in the right-most panel in Figure A2. The simulation results show that the small positive gap in marginal completion rates across quotas is consistent with screening costs.

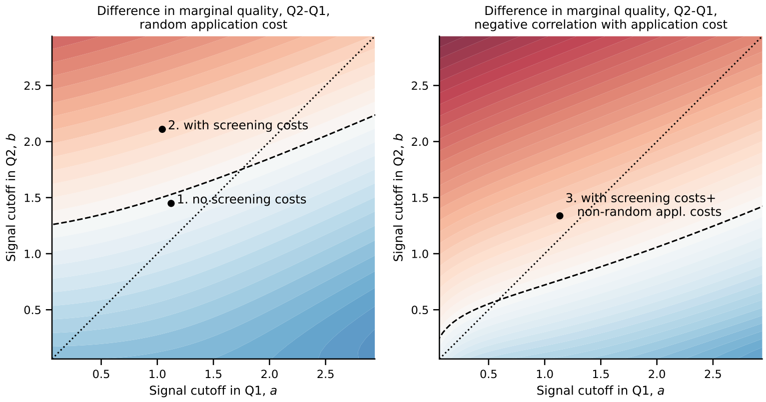


Figure A2: Marginal quality gap in cutoff space

Note: The figures show the gap in quality of marginal applicants, $E[y|\sigma_1 < a, \sigma_2 = b, Q2] - E[y|\sigma_1 = a, (Q2 \wedge \sigma_2 < b) \vee \neg Q2]$ as a function of cutoffs in Quota 1, a, and Quota 2, b. The colors are equally scaled across figures. Red indicates a higher than zero gap. The dashed line indicates a gap of zero. The circles indicate the optimum of the programs objective function in each scenario.

B Additional figures and tables

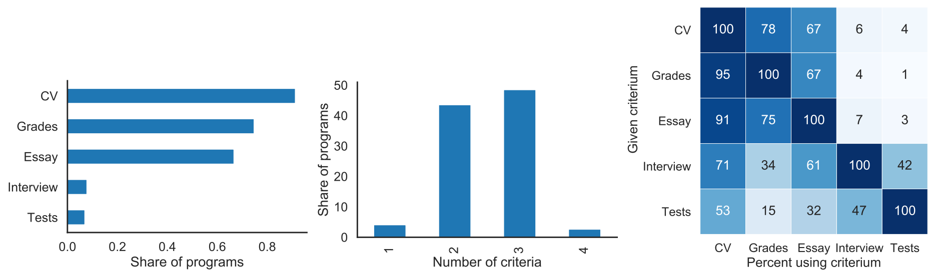
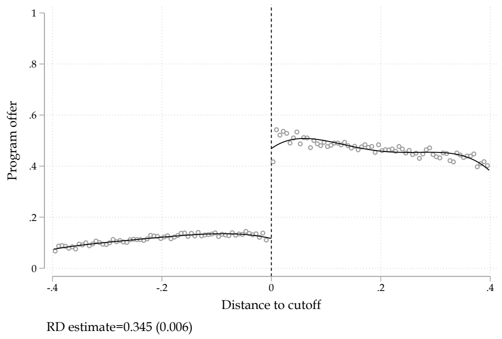
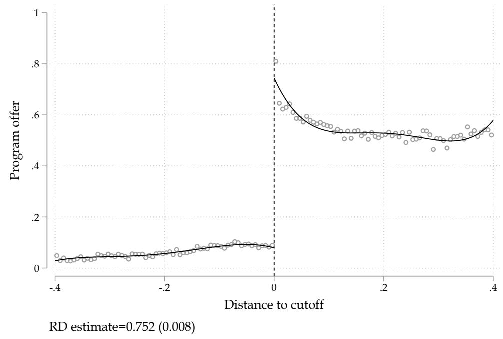


Figure B1: Combination of criteria

Note: The figure shows the use of criteria across programs as recorded by the Ministry of Higher Education and Science, see UFM (2020).



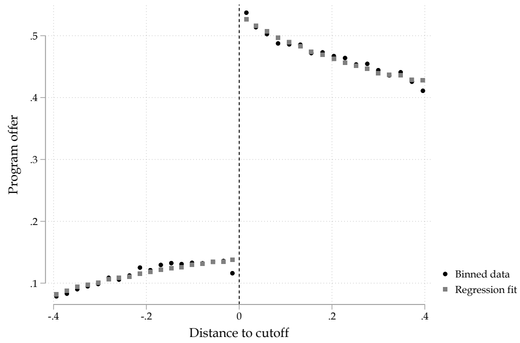
(a) GPA-based admissions (Quota 1)



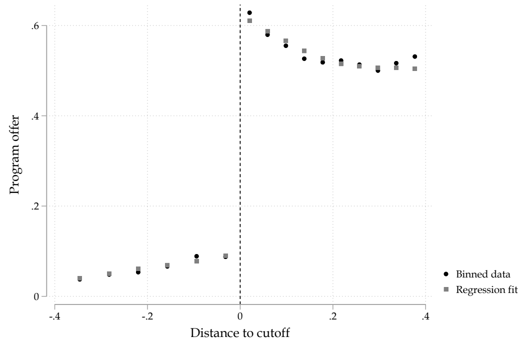
(b) Holistic admissions (Quota 2)

Figure B2: Program offer rates in GPA-based (Q1) and holistic admissions (Q2) – All applicants

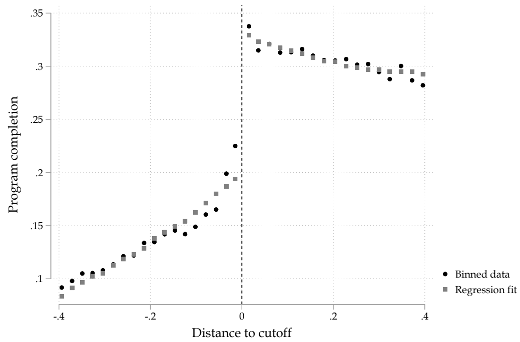
Note: Figures admission offer rates for all applicants in Quota 1 and 2. RD point estimates of value added, $Y^1 - Y^0$, with standard errors are presented below the graphs. Graphs and estimates are constructed using *rdplot* and *rdrobust* packages in Stata. Corresponding results for educational outcomes are shown in Appendix Figure B3.



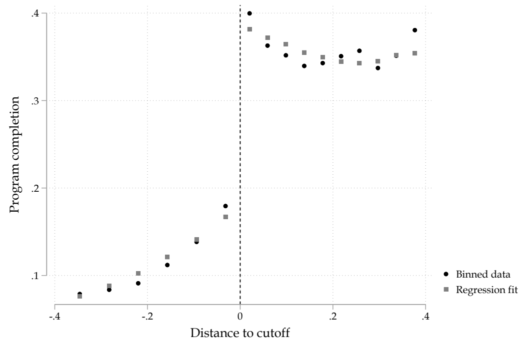
(a) Admission, Quota 1



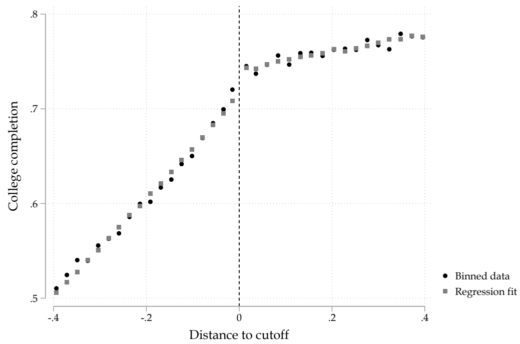
(b) Admission, Quota 2



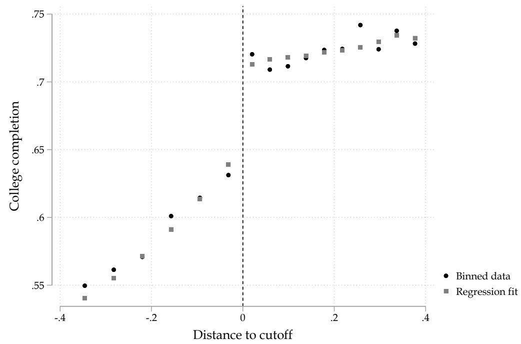
(c) Program completion, Quota 1



(d) Program completion, Quota 2



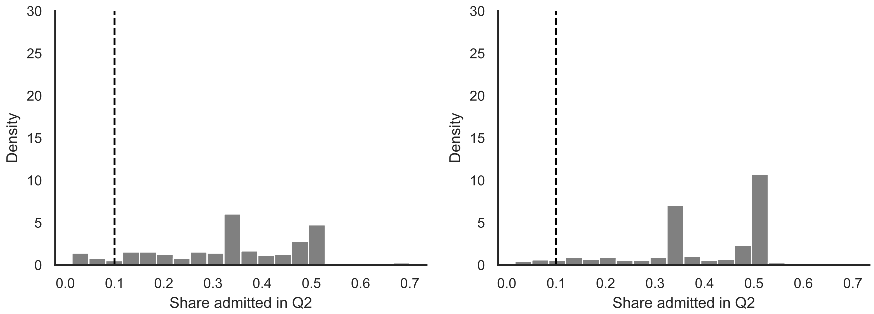
(e) College completion, Quota 1



(f) College completion, Quota 2

Figure B3: Fit of non-parametric and parametric RDD

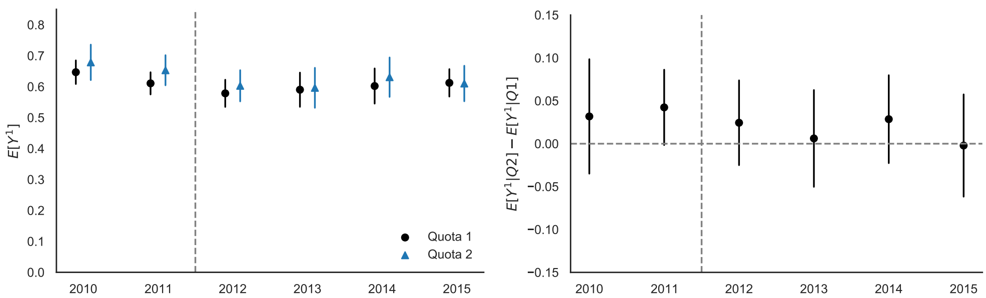
The figures display the fit of the first stages and reduced forms of the non-parametric models and the regression-based models for applicants in Quota 1 and 2. Non-parametric models are estimated using the *rdrobust*-package in Stata, while the parametric models are estimated with a quadratic spline and program-quota-year fixed effects. Bins with less than 10 applicants are not displayed.



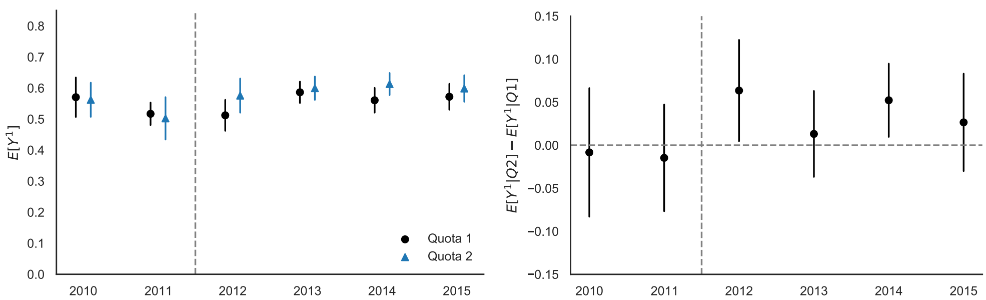
(a) Non-academic programs, 2010-2011 (b) Non-academic programs, 2012-2015

Figure B4: Share of applicants admitted in Q2

Share of admitted applicants admitted using alternative evaluation on the program-year level. The dashed line indicates the ceiling on quota share which was lifted in 2012. A few programs have admittance over 80 percent, which are omitted from this graph. For comparability, all figures are normalized and use the same range and number of bins.



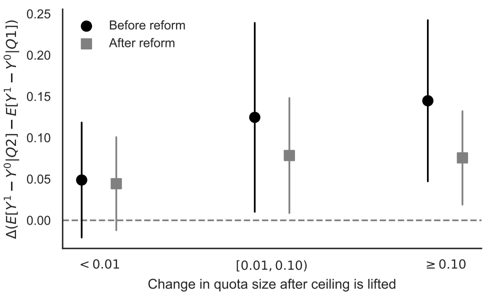
(a) Academic programs, levels (b) Academic programs, difference



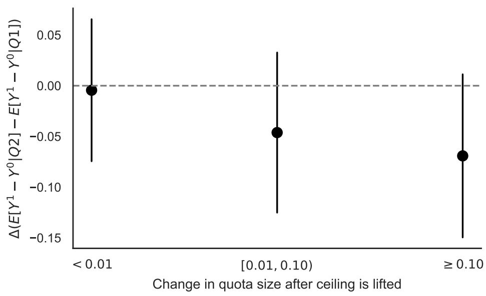
(c) Non-academic programs, levels (d) Non-academic programs, difference

Figure B5: Completion rate of marginal applicants, non-academic programs

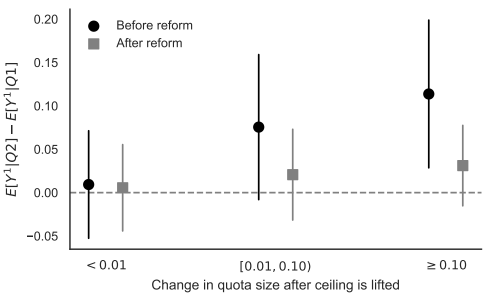
Note: The figure shows estimates of marginal completion rates for each year with 95 percent confidence intervals. The dashed line indicates that the ceiling on quota share was lifted in 2012. The right panel shows the difference between marginal completion rates in Quota 2 and Quota 1. Standard errors are clustered by program.



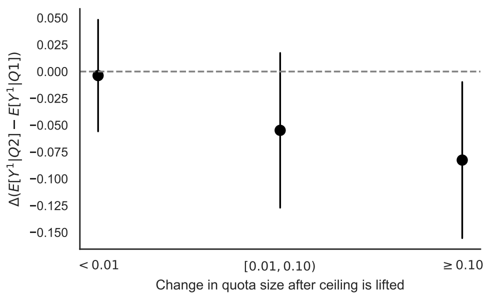
(a) Gap in $Y^1 - Y^0$ before and after reform



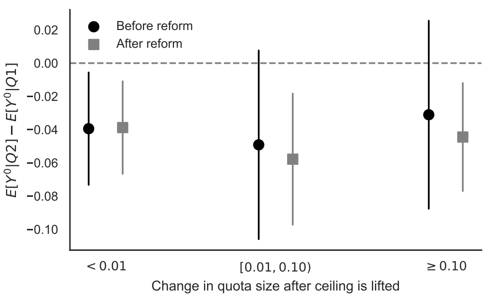
(b) Change in gap in $Y^1 - Y^0$



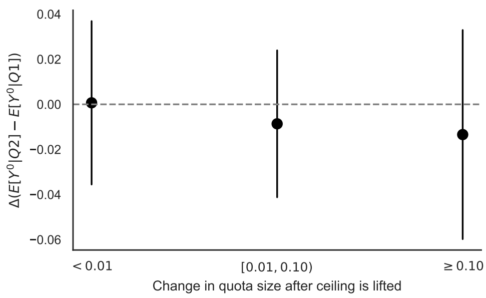
(c) Gap in Y^1 before and after reform



(d) Change in gap in Y^1



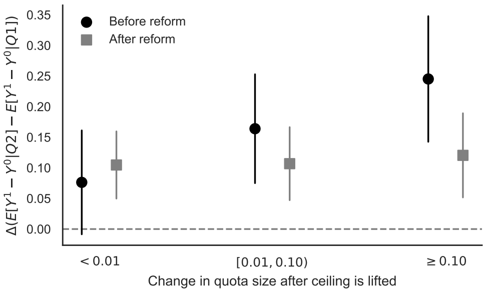
(e) Gap in Y^0 before and after reform



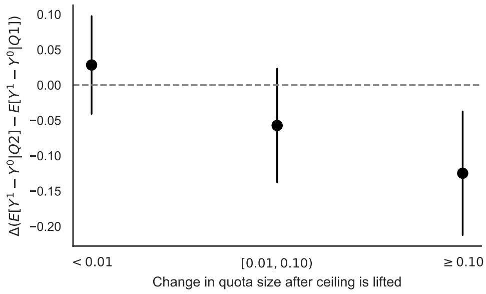
(f) Change in gap in Y^0

Figure B6: Program completion gap by intensity of constraint and before and after reform

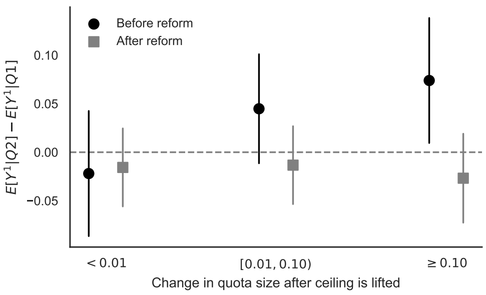
Note: This figure presents the gaps in average potential outcomes and value added in terms of program completion. We refer to the note in Figure 7 for detail.



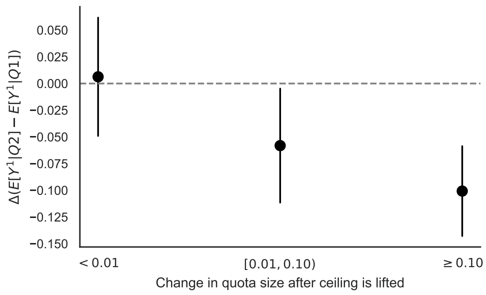
(a) Gap in $Y^1 - Y^0$ before and after reform



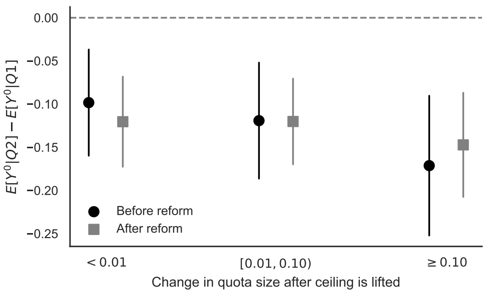
(b) Change in gap in $Y^1 - Y^0$



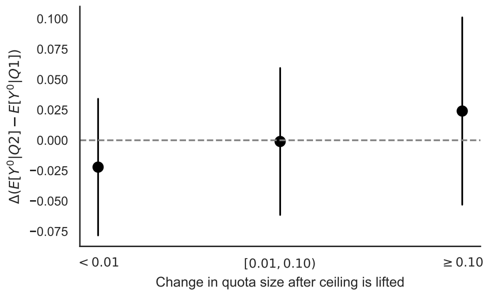
(c) Gap in Y^1 before and after reform



(d) Change in gap in Y^1



(e) Gap in Y^0 before and after reform



(f) Change in gap in Y^0

Figure B7: College completion gap by intensity of constraint and before and after reform

Note: This figure presents the gaps in average potential outcomes and value added in terms of program completion. We refer to the note in Figure 7 for detail.

Table B1: Bunching and balancing around the admission cutoffs, nonparametric

	(1) Female	(2) Immigrant	(3) SES	(4) GPA	(5) Apply to Q2
GPA-based (Q1)	-0.002	-0.002	0.001	-0.137	0.006
	(0.005)	(0.004)	(0.003)	(0.015)	(0.007)
Alternative (Q2)	-0.001	0.008	-0.006	0.001	
	(0.007)	(0.006)	(0.004)	(0.016)	

Note: The table contains validity check on the regression discontinuity design in Quota 1 and 2 using the —rdrobust– package in Stata pooling the data. Equivalent 2SLS estimates are displayed in Table 3 in the main text. Program-year fixed effects are not included.

Table B2: Potential program and college completion rates and value added - GPA-based admission vs. Alternative Evaluation, non-parametric fuzzy RDD

	Program, Y^0	Program, Y^1	Program, $Y^1 - Y^0$
Holistic (Q2)	0.224	0.584	0.349
	(0.007)	(0.006)	(0.01)
GPA-based (Q1)	0.346	0.552	0.204
	(0.019)	(0.007)	(0.023)
	College, Y^0	**College, Y^1**	**College, $Y^1 - Y^0$**
Holistic (Q2)	0.606	0.705	0.11
	(0.008)	(0.006)	(0.009)
GPA-based (Q1)	0.726	0.715	-0.018
	(0.015)	(0.006)	(0.017)

Note: The table contains estimated potential completion rates (Y^1) and value added ($Y^1 - Y^0$) with standard errors in parentheses. Standard errors are clustered by applicant. Models are estimated for program and college completion usingfuzzy RD estimated in Stata using the rdrobust-package.

Table B3: Effect of reweighting complier shares

	Q1		Q2	
	Baseline	Q2-weighted	Baseline	Q1-weighted
Program, Y^1	0.577 (0.004)	0.572 (0.009)	0.587 (0.005)	0.577 (0.020)
College, Y^1	0.734 (0.004)	0.734 (0.005)	0.706 (0.004)	0.701 (0.073)
College, $Y^1 - Y^0$	0.045 (0.007)	0.041 (0.032)	0.092 (0.007)	0.089 (0.078)

Note: The table presents a reweighing exercise to match complier shares across quotas. The first and third column present our baseline results from Table 4. Columns 2 present estimates in Quota 1 where we reweigh so that the complier shares in Q1 match Quota 2. Column 4 does the reverse and match complier shares in Q2 to Q1. Clustered standard errors are bootstrapped with 199 replications.

Table B4: Change in gaps from pre- and post-reform, academic programs

	(1) Program Y^1	(2) College $Y^1 - Y^0$	(3) Program Y^1	(4) College $Y^1 - Y^0$	(5) Program Y^1	(6) College $Y^1 - Y^0$
Admitted	0.627	0.056	0.634	0.047	0.613	0.062
	(0.018)	(0.022)	(0.025)	(0.031)	(0.024)	(0.033)
After reform × Admitted	-0.031	-0.019	-0.026	-0.009	-0.034	-0.034
	(0.016)	(0.016)	(0.021)	(0.024)	(0.026)	(0.024)
Q2 × Admitted	0.041	0.121	0.015	0.142	0.085	0.097
	(0.025)	(0.033)	(0.034)	(0.050)	(0.029)	(0.041)
After reform × Q2 × Admitted	-0.028	-0.013	-0.022	-0.042	-0.045	0.027
	(0.022)	(0.030)	(0.032)	(0.041)	(0.027)	(0.045)
Observations	458408	458408	246258	246258	212150	212150
Gap with restriction	.041 (.025)	.121 (.033)	.015 (.034)	.142 (.05)	.085 (.029)	.097 (.041)
Gap without restriction	.013 (.019)	.108 (.023)	-.007 (.026)	.099 (.035)	.04 (.022)	.124 (.036)
Gap closed (p-value)	0.478	0.000	0.788	0.006	0.079	0.001
Academic programs	YES	YES	YES	YES	YES	YES
Increase Q2-share			NO	NO	YES	YES

Note: The table shows the estimates of a a modification of the model in equation (5) estimated by 2SLS where the difference across quotas is calculated before and after 2012 where restrictions on Quota 2 was lifted. The models are stacked and all running variables are appropriately interacted with a post-indicator. The model is estimated with program-year-fixed effects and standard errors are clustered by program.

Table B5: Change in gaps from pre- and post-reform, non-academic programs

	(1) Program, Y^1	(2) College, $Y^1 - Y^0$
Admitted	0.539	0.003
	(0.016)	(0.023)
After reform × Admitted	0.021	0.014
	(0.021)	(0.026)
Q2 × Admitted	-0.009	0.047
	(0.020)	(0.034)
After reform × Q2 × Admitted	0.044	-0.014
	(0.025)	(0.037)
Observations	354833	354833
Gap with restriction	-.009 (.02)	.047 (.034)
Gap without restriction	.035 (.014)	.033 (.021)
Gap closed (p-value)	0.016	0.111
Academic programs	NO	NO
Increase Q2-share		

Note: The table shows the estimates of a a modification of the model in equation (5) estimated by 2SLS where the difference across quotas is calculated before and after 2012 where restrictions on Quota 2 was lifted. The models are stacked and all running variables are appropriately interacted with a post-indicator. The model is estimated with program-year-fixed effects and standard errors are clustered on by program.

Table B6: Test of differences in completion gaps by program characteristics: usage of Quota 2

Contrast	Program Y^1	College Y^1	College $Y^1 - Y^0$
≤.15 - (.15,.4]	0.003 (p=0.855)	0.008 (p=0.627)	0.060 (p=0.023)
≤.15 - >.4	-0.019 (p=0.302)	0.020 (p=0.224)	0.102 (p=0.000)
(.15,.4] - >.4	-0.022 (p=0.182)	0.012 (p=0.411)	0.042 (p=0.091)

Note: The table shows formal test of differences in marginal gaps displayed in Figure 8a. Standard errors are clustered on applicant-level. Details are described in the note to Figure 8.

Table B7: Test of differences in completion gaps by program characteristics: Selectivity

Contrast	Program Y^1	College Y^1	College $Y^1 - Y^0$
High - Low	-0.027 (p=0.136)	-0.004 (p=0.788)	0.039 (p=0.161)
High - Moderate	-0.040 (p=0.027)	-0.010 (p=0.516)	-0.002 (p=0.929)
High - Very low	0.031 (p=0.296)	0.034 (p=0.223)	-0.010 (p=0.843)
Low - Moderate	-0.012 (p=0.448)	-0.006 (p=0.695)	-0.041 (p=0.109)
Low - Very low	0.058 (p=0.040)	0.038 (p=0.161)	-0.049 (p=0.318)
Moderate - Very low	0.070 (p=0.012)	0.044 (p=0.102)	-0.007 (p=0.878)

Note: The table shows formal test of differences in marginal gaps displayed in Figure 8b. Standard errors are clustered on applicant-level. Details are described in the note to Figure 8.

Table B8: Test of differences in completion gaps by program characteristics: Criteria

Contrast	Program Y^1	College Y^1	College $Y^1 - Y^0$
Essay - Grades	0.037 (p=0.000)	0.023 (p=0.000)	0.013 (p=0.205)
Essay - Interview	-0.039 (p=0.249)	-0.012 (p=0.693)	0.046 (p=0.323)
Essay - CV	0.030 (p=0.000)	0.022 (p=0.000)	0.029 (p=0.000)
Essay - Test	-0.021 (p=0.515)	-0.045 (p=0.109)	0.010 (p=0.833)
Grades - Interview	-0.076 (p=0.022)	-0.034 (p=0.237)	0.034 (p=0.466)
Grades - CV	-0.007 (p=0.055)	-0.001 (p=0.707)	0.017 (p=0.003)
Grades - Test	-0.058 (p=0.069)	-0.068 (p=0.015)	-0.003 (p=0.947)
Interview - CV	0.069 (p=0.036)	0.033 (p=0.251)	-0.017 (p=0.716)
Interview - Test	0.017 (p=0.491)	-0.034 (p=0.135)	-0.037 (p=0.316)
CV - Test	-0.051 (p=0.105)	-0.067 (p=0.016)	-0.020 (p=0.654)

Note: The table shows formal test of differences in marginal gaps displayed in Figure 8c. As each program uses multiple criteria, programs enter into each subset multiple times. Note that programs use multiple criteria and are therefore included multiple times. Standard errors are clustered on applicant. Details are described in the note to Figure 8.

Table B9: RDD estimates with varying bandwidth and specification

	Order of poly.	Bandwidth	Slopes	Baseline	Program, Y^0	Program, Y^1	Program, $Y^1 - Y^0$	College, Y^0	College, Y^1	College, $Y^1 - Y^0$
Q1	1				0.193	0.568	0.376	0.685	0.731	0.045
					(0.003)	(0.003)	(0.004)	(0.006)	(0.003)	(0.007)
Q1	2			X	0.219	0.577	0.357	0.69	0.734	0.044
					(0.003)	(0.004)	(0.006)	(0.006)	(0.004)	(0.007)
Q1	3				0.235	0.57	0.335	0.71	0.728	0.018
					(0.004)	(0.005)	(0.006)	(0.007)	(0.004)	(0.008)
Q1	1	P-Q-Y			0.23	0.569	0.339	0.689	0.728	0.039
					(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.007)
Q1	1	P-Q-Y	P-Q		0.237	0.548	0.311	0.706	0.71	0.004
					(0.005)	(0.006)	(0.007)	(0.007)	(0.005)	(0.009)
Q2	1				0.197	0.607	0.41	0.587	0.724	0.137
					(0.003)	(0.004)	(0.005)	(0.006)	(0.004)	(0.007)
Q2	2			X	0.204	0.587	0.383	0.614	0.706	0.092
					(0.003)	(0.005)	(0.006)	(0.006)	(0.004)	(0.007)
Q2	3				0.213	0.585	0.372	0.614	0.705	0.091
					(0.004)	(0.005)	(0.007)	(0.007)	(0.005)	(0.008)
Q2	1	P-Q-Y			0.237	0.589	0.352	0.577	0.715	0.138
					(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.008)
Q2	1	P-Q-Y	P-Q		0.24	0.549	0.309	0.612	0.673	0.061
					(0.008)	(0.008)	(0.011)	(0.011)	(0.007)	(0.013)
Q2-Q1	1				0.004	0.038	0.034	-0.099	-0.007	0.092
					(0.004)	(0.005)	(0.007)	(0.008)	(0.005)	(0.009)
Q2-Q1	2			X	-0.015	0.011	0.026	-0.076	-0.028	0.048
					(0.005)	(0.006)	(0.008)	(0.009)	(0.006)	(0.01)
Q2-Q1	3				-0.021	0.015	0.037	-0.095	-0.022	0.073
					(0.005)	(0.007)	(0.009)	(0.009)	(0.007)	(0.011)
Q2-Q1	1	P-Q-Y			0.007	0.019	0.012	-0.112	-0.013	0.099
					(0.006)	(0.007)	(0.009)	(0.009)	(0.006)	(0.011)
Q2-Q1	1	P-Q-Y	P-Q		0.003	0.001	-0.002	-0.094	-0.036	0.058
					(0.009)	(0.01)	(0.013)	(0.013)	(0.009)	(0.015)

Note: The table shows parameter estimates for all potential outcomes and standard errors in parenthesis for RDD estimates with varying bandwidth different orders of the polynomials in the running variables. The first column together with columns 6-20 identifies the estimand. All rows which share values in columns 2-5 are estimated in a stacked design to ensure correct standard errors. The second column show the order of the polynomial use for the spline of the running variable. Specifications denoted by "P-Q-T" in the bandwidth column are estimated using program-quota-year specific optimal bandwidths calculated using RDrobust. Specifications denoted by "P-Q" in the slope column are estimated using program-quota-specific linear splines. The baseline estimates from the main paper are marked by X in the Baseline column. Standard errors are clustered on applicant level.

Table B10: RDD estimates with varying bandwidth and specification, by Quota 2 share

	Specification				≤.15			(.15,.4]			>.4		
	Order of poly.	Bandwidth	Slopes	Baseline	Program, Y^1	College, Y^1	College, Y^1-Y^0	Program, Y^1	College, Y^1	College, Y^1-Y^0	Program, Y^1	College, Y^1	College, Y^1-Y^0
Q1	1				0.577	0.72	0.059	0.567	0.748	0.064	0.575	0.746	0.029
					(0.005)	(0.004)	(0.009)	(0.006)	(0.005)	(0.011)	(0.008)	(0.007)	(0.014)
Q1	2			X	0.587	0.726	0.027	0.561	0.732	0.033	0.575	0.745	0.041
					(0.006)	(0.006)	(0.011)	(0.007)	(0.006)	(0.012)	(0.01)	(0.009)	(0.015)
Q1	3				0.575	0.717	0.007	0.564	0.733	0.014	0.568	0.733	0.013
					(0.008)	(0.007)	(0.013)	(0.008)	(0.007)	(0.012)	(0.011)	(0.009)	(0.015)
Q1	1	P-Q-Y			0.572	0.709	0.031	0.575	0.744	0.059	0.571	0.741	0.012
					(0.007)	(0.006)	(0.011)	(0.007)	(0.007)	(0.011)	(0.009)	(0.008)	(0.014)
Q1	1	P-Q-Y	P-Q		0.541	0.683	0.013	0.539	0.72	0.002	0.568	0.728	-0.006
					(0.009)	(0.009)	(0.014)	(0.009)	(0.008)	(0.014)	(0.012)	(0.01)	(0.017)
Q2	1				0.603	0.709	0.142	0.581	0.721	0.118	0.62	0.726	0.114
					(0.009)	(0.009)	(0.014)	(0.007)	(0.007)	(0.012)	(0.005)	(0.005)	(0.009)
Q2	2			X	0.594	0.708	0.149	0.564	0.705	0.095	0.6	0.706	0.061
					(0.012)	(0.011)	(0.017)	(0.008)	(0.008)	(0.014)	(0.006)	(0.006)	(0.01)
Q2	3				0.597	0.716	0.195	0.579	0.719	0.105	0.599	0.705	0.048
					(0.014)	(0.013)	(0.02)	(0.01)	(0.009)	(0.015)	(0.008)	(0.007)	(0.012)
Q2	1	P-Q-Y			0.585	0.706	0.184	0.573	0.724	0.138	0.6	0.709	0.098
Q2													
					(0.012)	(0.011)	(0.018)	(0.009)	(0.008)	(0.015)	(0.007)	(0.006)	(0.011)
Q2	1	P-Q-Y	P-Q		0.554	0.68	0.121	0.531	0.687	0.072	0.557	0.663	0.029
					(0.019)	(0.018)	(0.03)	(0.014)	(0.013)	(0.024)	(0.01)	(0.01)	(0.017)
Q2-Q1	1				0.027	-0.011	0.083	0.014	-0.027	0.054	0.045	-0.02	0.085
					(0.011)	(0.01)	(0.016)	(0.01)	(0.009)	(0.016)	(0.01)	(0.009)	(0.017)
Q2-Q1	2			X	0.007	-0.018	0.122	0.004	-0.026	0.062	0.026	-0.038	0.02
					(0.014)	(0.013)	(0.02)	(0.011)	(0.01)	(0.018)	(0.012)	(0.011)	(0.018)
Q2-Q1	3				0.022	-0.001	0.189	0.015	-0.013	0.091	0.031	-0.028	0.034
					(0.016)	(0.015)	(0.023)	(0.013)	(0.012)	(0.02)	(0.013)	(0.012)	(0.019)
Q2-Q1	1	P-Q-Y			0.013	-0.003	0.154	-0.001	-0.02	0.079	0.029	-0.032	0.086
					(0.014)	(0.013)	(0.021)	(0.012)	(0.011)	(0.019)	(0.012)	(0.011)	(0.018)
Q2-Q1	1	P-Q-Y	P-Q		0.013	-0.003	0.108	-0.007	-0.034	0.07	-0.011	-0.065	0.035
					(0.021)	(0.02)	(0.033)	(0.017)	(0.016)	(0.027)	(0.016)	(0.014)	(0.024)

Note: The table shows parameter estimates for standard errors in parenthesis for RDD estimates with varying bandwidth different orders of the polynomials in the running variables. The first column together with columns 6-20 identifies the estimand. All rows which share values in columns 2-5 are estimated in a stacked design to ensure correct standard errors. The second column show the order of the polynomial use for the spline of the running variable. Specifications denoted by “P-Q-T” in the bandwidth column are estimated using program-quota-year specific optimal bandwidths calculated using RDrobust. Specifications denoted by “P-Q” in the slope column are estimated using program-quota-specific linear splines. The baseline estimates in figure 8 are marked by “X” in the Baseline column. Standard errors are clustered on applicant level.

Table B11: RDD estimates with varying bandwidth and specification, by selectivity

	Specification				Very low			Low			Moderate			High		
	Order of poly.	Bandwidth	Slope	Baseline	Program Y^1	College Y^1	College $Y^1 - Y^0$	Program Y^1	College Y^1	College $Y^1 - Y^0$	Program Y^1	College Y^1	College $Y^1 - Y^0$	Program Y^1	College Y^1	College $Y^1 - Y^0$
Q1	1				0.5	0.647	0.034	0.506	0.682	0.02	0.556	0.718	0.048	0.683	0.826	0.08
					(0.016)	(0.015)	(0.027)	(0.007)	(0.007)	(0.014)	(0.005)	(0.005)	(0.01)	(0.007)	(0.006)	(0.013)
Q1	2			X	0.501	0.645	-0.0	0.511	0.68	0.041	0.562	0.72	0.037	0.673	0.822	0.051
					(0.018)	(0.017)	(0.029)	(0.009)	(0.008)	(0.015)	(0.007)	(0.006)	(0.011)	(0.008)	(0.007)	(0.014)
Q1	3				0.495	0.641	-0.003	0.502	0.675	0.012	0.565	0.722	0.031	0.661	0.812	0.011
					(0.02)	(0.019)	(0.032)	(0.01)	(0.009)	(0.015)	(0.008)	(0.007)	(0.012)	(0.01)	(0.008)	(0.015)
Q1	1	P-Q-Y			0.539	0.681	0.079	0.516	0.689	0.022	0.563	0.718	0.032	0.686	0.814	0.048
					(0.019)	(0.018)	(0.029)	(0.009)	(0.008)	(0.014)	(0.007)	(0.006)	(0.011)	(0.009)	(0.008)	(0.014)
Q1	1	P-Q-Y	P-Q		0.494	0.638	0.023	0.516	0.679	0.001	0.558	0.714	0.003	0.6	0.779	0.002
					(0.024)	(0.023)	(0.037)	(0.011)	(0.01)	(0.017)	(0.009)	(0.008)	(0.013)	(0.012)	(0.01)	(0.016)
Q2	1				0.507	0.626	0.143	0.561	0.679	0.128	0.624	0.733	0.144	0.682	0.809	0.15
					(0.015)	(0.015)	(0.029)	(0.006)	(0.006)	(0.011)	(0.007)	(0.006)	(0.011)	(0.009)	(0.008)	(0.013)
Q2	2			X	0.477	0.595	0.075	0.544	0.669	0.068	0.608	0.715	0.105	0.679	0.806	0.117
					(0.018)	(0.018)	(0.033)	(0.008)	(0.007)	(0.014)	(0.009)	(0.008)	(0.012)	(0.011)	(0.01)	(0.014)
Q2	3				0.457	0.579	0.037	0.541	0.669	0.064	0.602	0.707	0.115	0.668	0.79	0.123
					(0.021)	(0.021)	(0.039)	(0.009)	(0.009)	(0.016)	(0.01)	(0.009)	(0.014)	(0.012)	(0.011)	(0.016)
Q2	1	P-Q-Y			0.503	0.631	0.133	0.567	0.686	0.11	0.611	0.725	0.133	0.642	0.804	0.183
					(0.017)	(0.017)	(0.032)	(0.008)	(0.007)	(0.014)	(0.01)	(0.009)	(0.014)	(0.012)	(0.01)	(0.016)
Q2	1	P-Q-Y	P-Q		0.447	0.564	0.068	0.544	0.668	0.046	0.568	0.682	0.065	0.603	0.76	0.095
					(0.021)	(0.022)	(0.042)	(0.011)	(0.011)	(0.02)	(0.014)	(0.014)	(0.022)	(0.02)	(0.019)	(0.029)
Q2-Q1	1				0.007	-0.021	0.109	0.055	-0.002	0.108	0.068	0.015	0.096	-0.001	-0.016	0.069
					(0.022)	(0.022)	(0.04)	(0.01)	(0.009)	(0.018)	(0.009)	(0.008)	(0.014)	(0.012)	(0.01)	(0.017)
Q2-Q1	2			X	-0.024	-0.05	0.076	0.033	-0.011	0.027	0.046	-0.005	0.068	0.006	-0.016	0.066
					(0.026)	(0.025)	(0.044)	(0.012)	(0.011)	(0.02)	(0.011)	(0.01)	(0.017)	(0.014)	(0.012)	(0.019)
Q2-Q1	3				-0.037	-0.062	0.04	0.039	-0.006	0.051	0.037	-0.015	0.085	0.008	-0.021	0.111
					(0.029)	(0.029)	(0.05)	(0.013)	(0.013)	(0.022)	(0.013)	(0.012)	(0.018)	(0.016)	(0.014)	(0.022)
Q2-Q1	1	P-Q-Y			-0.036	-0.05	0.054	0.051	-0.003	0.088	0.048	0.006	0.102	-0.044	-0.01	0.135
					(0.026)	(0.025)	(0.043)	(0.012)	(0.011)	(0.02)	(0.012)	(0.011)	(0.018)	(0.015)	(0.013)	(0.021)
Q2-Q1	1	P-Q-Y	P-Q		-0.047	-0.074	0.045	0.028	-0.012	0.045	0.01	-0.032	0.061	0.003	-0.019	0.093
					(0.032)	(0.032)	(0.056)	(0.016)	(0.015)	(0.026)	(0.017)	(0.016)	(0.026)	(0.024)	(0.021)	(0.033)

Note: The table shows parameter estimates for standard errors in parenthesis for RDD estimates with varying bandwidth different orders of the polynomials in the running variables. The first column together with columns 6-20 identifies the estimand. All rows which share values in columns 2-5 are estimated in a stacked design to ensure correct standard errors. The second column show the order of the polynomial use for the spline of the running variable. Specifications denoted by “P-Q-T” in the bandwidth column are estimated using program-quota-year specific optimal bandwidths calculated using RDrobust. Specifications denoted by “P-Q” in the slope column are estimated using program-quota-specific linear splines. The baseline estimates in figure 8 are marked by “X” in the Baseline column. Standard errors are clustered on applicant level.

Table B12: RDD estimates with varying bandwidth and specification, by criteria

	Specification				CV			Grades			Essay			Interview			Test		
	Order of poly.	Bandwidth	Slope	Baseline	Program Y^1	College Y^1	College Y^1-Y^0	Program Y^1	College Y^1	College Y^1-Y^0	Program Y^1	College Y^1	College Y^1-Y^0	Program Y^1	College Y^1	College Y^1-Y^0	Program Y^1	College Y^1	College Y^1-Y^0
Q1	1				0.572	0.731	0.038	0.57	0.729	0.036	0.56	0.733	0.022	0.631	0.779	0.147	0.587	0.77	0.226
					(0.004)	(0.003)	(0.007)	(0.004)	(0.003)	(0.007)	(0.005)	(0.004)	(0.008)	(0.022)	(0.018)	(0.035)	(0.02)	(0.018)	(0.032)
Q1	2			X	0.582	0.736	0.043	0.581	0.734	0.04	0.576	0.737	0.03	0.657	0.808	0.129	0.556	0.771	0.129
					(0.004)	(0.004)	(0.007)	(0.005)	(0.004)	(0.008)	(0.006)	(0.005)	(0.009)	(0.022)	(0.019)	(0.035)	(0.021)	(0.018)	(0.031)
Q1	3				0.572	0.727	0.016	0.572	0.727	0.017	0.561	0.725	0.005	0.644	0.794	0.05	0.563	0.778	0.048
					(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.008)	(0.006)	(0.006)	(0.01)	(0.023)	(0.019)	(0.034)	(0.022)	(0.02)	(0.032)
Q1	1	P-Q-Y			0.57	0.729	0.036	0.568	0.726	0.035	0.559	0.726	0.016	0.649	0.784	0.076	0.577	0.775	0.137
					(0.005)	(0.004)	(0.007)	(0.005)	(0.004)	(0.008)	(0.006)	(0.005)	(0.009)	(0.022)	(0.019)	(0.035)	(0.02)	(0.018)	(0.031)
Q1	1	P-Q-Y	P-Q		0.557	0.71	0.0	0.552	0.707	-0.002	0.54	0.705	-0.007	0.624	0.776	0.014	0.447	0.746	0.095
					(0.006)	(0.005)	(0.009)	(0.006)	(0.006)	(0.01)	(0.008)	(0.007)	(0.012)	(0.027)	(0.023)	(0.04)	(0.024)	(0.023)	(0.035)
Q2	1				0.609	0.721	0.13	0.599	0.717	0.126	0.625	0.736	0.132	0.764	0.83	0.186	0.621	0.827	0.247
					(0.004)	(0.004)	(0.007)	(0.005)	(0.004)	(0.008)	(0.005)	(0.005)	(0.008)	(0.018)	(0.016)	(0.025)	(0.017)	(0.014)	(0.026)
Q2	2			X	0.589	0.702	0.083	0.582	0.7	0.097	0.613	0.725	0.099	0.734	0.808	0.152	0.615	0.805	0.189
					(0.005)	(0.005)	(0.007)	(0.006)	(0.005)	(0.009)	(0.006)	(0.005)	(0.008)	(0.023)	(0.02)	(0.03)	(0.022)	(0.019)	(0.031)
Q2	3				0.587	0.701	0.082	0.585	0.703	0.114	0.614	0.723	0.099	0.729	0.788	0.138	0.65	0.794	0.126
					(0.006)	(0.005)	(0.008)	(0.006)	(0.006)	(0.01)	(0.007)	(0.006)	(0.009)	(0.026)	(0.024)	(0.034)	(0.026)	(0.023)	(0.036)
Q2	1	P-Q-Y			0.597	0.712	0.128	0.592	0.713	0.142	0.613	0.725	0.123	0.758	0.813	0.084	0.638	0.809	0.14
					(0.005)	(0.005)	(0.008)	(0.006)	(0.005)	(0.01)	(0.006)	(0.006)	(0.01)	(0.027)	(0.024)	(0.046)	(0.023)	(0.019)	(0.034)
Q2	1	P-Q-Y	P-Q		0.556	0.671	0.053	0.548	0.669	0.073	0.572	0.683	0.051	0.741	0.789	0.044	0.488	0.807	0.146
					(0.008)	(0.008)	(0.013)	(0.009)	(0.009)	(0.015)	(0.01)	(0.01)	(0.016)	(0.041)	(0.038)	(0.064)	(0.033)	(0.033)	(0.054)
Q2-Q1	1				0.037	-0.01	0.092	0.03	-0.013	0.09	0.065	0.004	0.11	0.134	0.051	0.039	0.034	0.056	0.021
					(0.006)	(0.005)	(0.009)	(0.006)	(0.006)	(0.01)	(0.007)	(0.006)	(0.011)	(0.029)	(0.026)	(0.043)	(0.027)	(0.024)	(0.04)
Q2-Q1	2			X	0.007	-0.033	0.04	0.001	-0.035	0.057	0.038	-0.012	0.069	0.076	-0.0	0.023	0.059	0.034	0.06
					(0.007)	(0.006)	(0.01)	(0.007)	(0.007)	(0.012)	(0.008)	(0.007)	(0.012)	(0.033)	(0.029)	(0.046)	(0.031)	(0.027)	(0.044)
Q2-Q1	3				0.015	-0.026	0.066	0.013	-0.024	0.097	0.053	-0.002	0.093	0.085	-0.006	0.088	0.087	0.016	0.078
					(0.008)	(0.007)	(0.012)	(0.008)	(0.008)	(0.013)	(0.009)	(0.008)	(0.014)	(0.035)	(0.031)	(0.048)	(0.035)	(0.03)	(0.048)
Q2-Q1	1	P-Q-Y			0.026	-0.017	0.092	0.024	-0.013	0.107	0.054	-0.001	0.107	0.108	0.029	0.009	0.06	0.034	0.004
					(0.007)	(0.007)	(0.011)	(0.008)	(0.007)	(0.012)	(0.009)	(0.008)	(0.013)	(0.035)	(0.03)	(0.057)	(0.031)	(0.026)	(0.045)
Q2-Q1	1	P-Q-Y	P-Q		-0.002	-0.039	0.053	-0.004	-0.038	0.075	0.032	-0.022	0.058	0.118	0.013	0.03	0.041	0.061	0.051
					(0.01)	(0.009)	(0.016)	(0.011)	(0.01)	(0.018)	(0.013)	(0.012)	(0.02)	(0.049)	(0.044)	(0.075)	(0.041)	(0.04)	(0.063)

Note: The table shows parameter estimates for standard errors in parenthesis for RDD estimates with varying bandwidth different orders of the polynomials in the running variables. The first column together with columns 6-20 identifies the estimand. All rows which share values in columns 2-5 are estimated in a stacked design to ensure correct standard errors. The second column show the order of the polynomial use for the spline of the running variable. Specifications denoted by “P-Q-T” in the bandwidth column are estimated using program-quota-year specific optimal bandwidths calculated using RDrobust. Specifications denoted by “P-Q” in the slope column are estimated using program-quota-specific linear splines. The baseline estimates in figure 8 are marked by “X” in the Baseline column. Standard errors are clustered on applicant level.

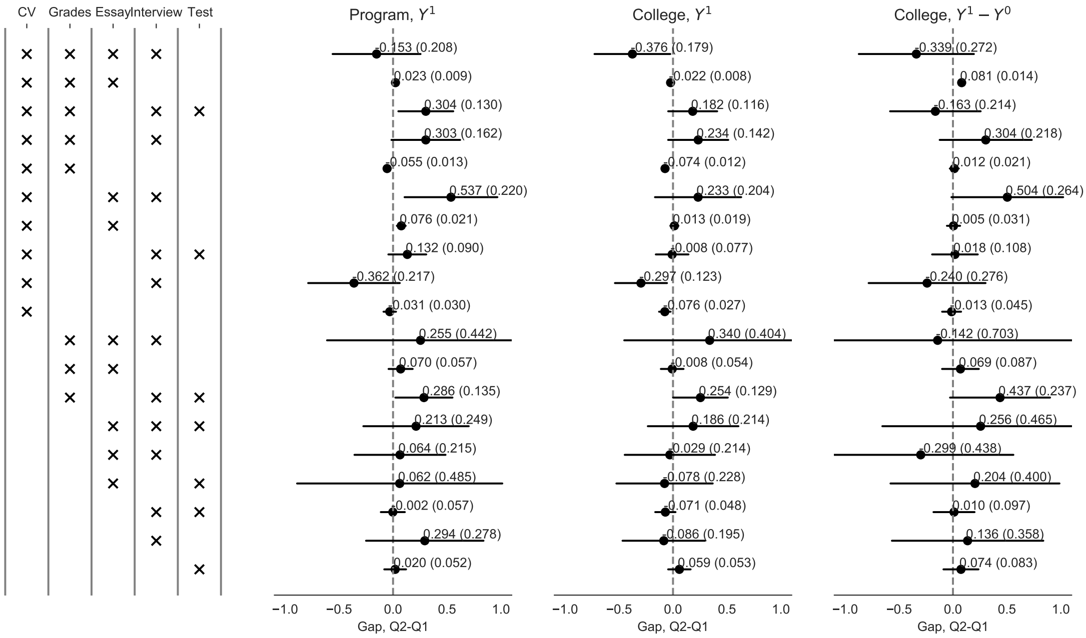


Figure B8: Difference in completion rates and value added, Holistic - GPA, by criteria

Note: The figures reproduce results from Table 4 for different subsets of programs. The leftmost figure shows differences between marginal program completion rates between holistic admission (Q2) and GPA-based admission (Q1). The middle figures show the same for overall college completion rates. The right-most figures show value added in terms of college completion rates. Parameter estimates are shown in gray with standard errors in parentheses. Standard errors are clustered on program-year level. Programs use multiple criteria and the sets of programs behind each estimates are overlapping. Appendix Figure

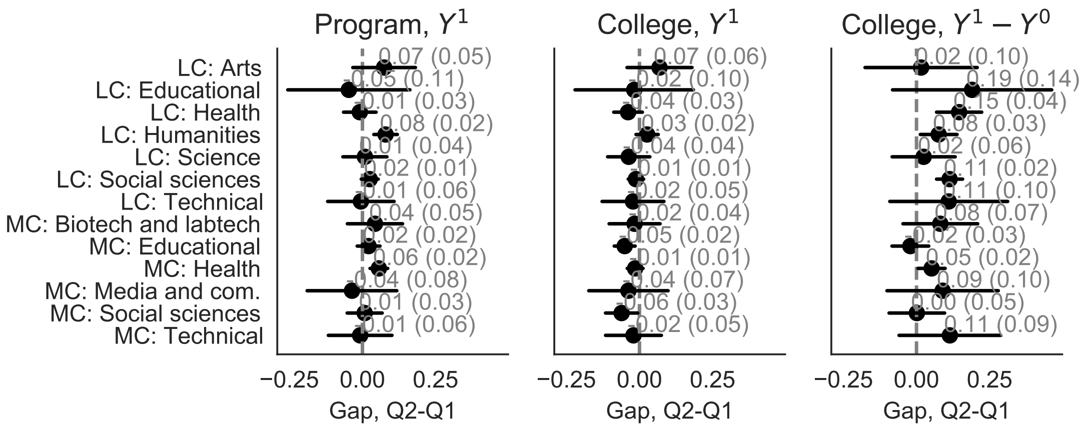


Figure B9: Difference in completion rates and value added, Holistic - GPA, by field

Note: The figures reproduce results from Table 4 for different subsets of programs. Short programs are collapsed into a single category. The leftmost figure shows differences between marginal program completion rates between holistic admission (Q2) and GPA-based admission (Q1). The middle figures show the same for overall college completion rates. The right-most figures show value added in terms of college completion rates. Parameter estimates are shown in gray with standard errors in parentheses. Standard errors are clustered on program-year level.

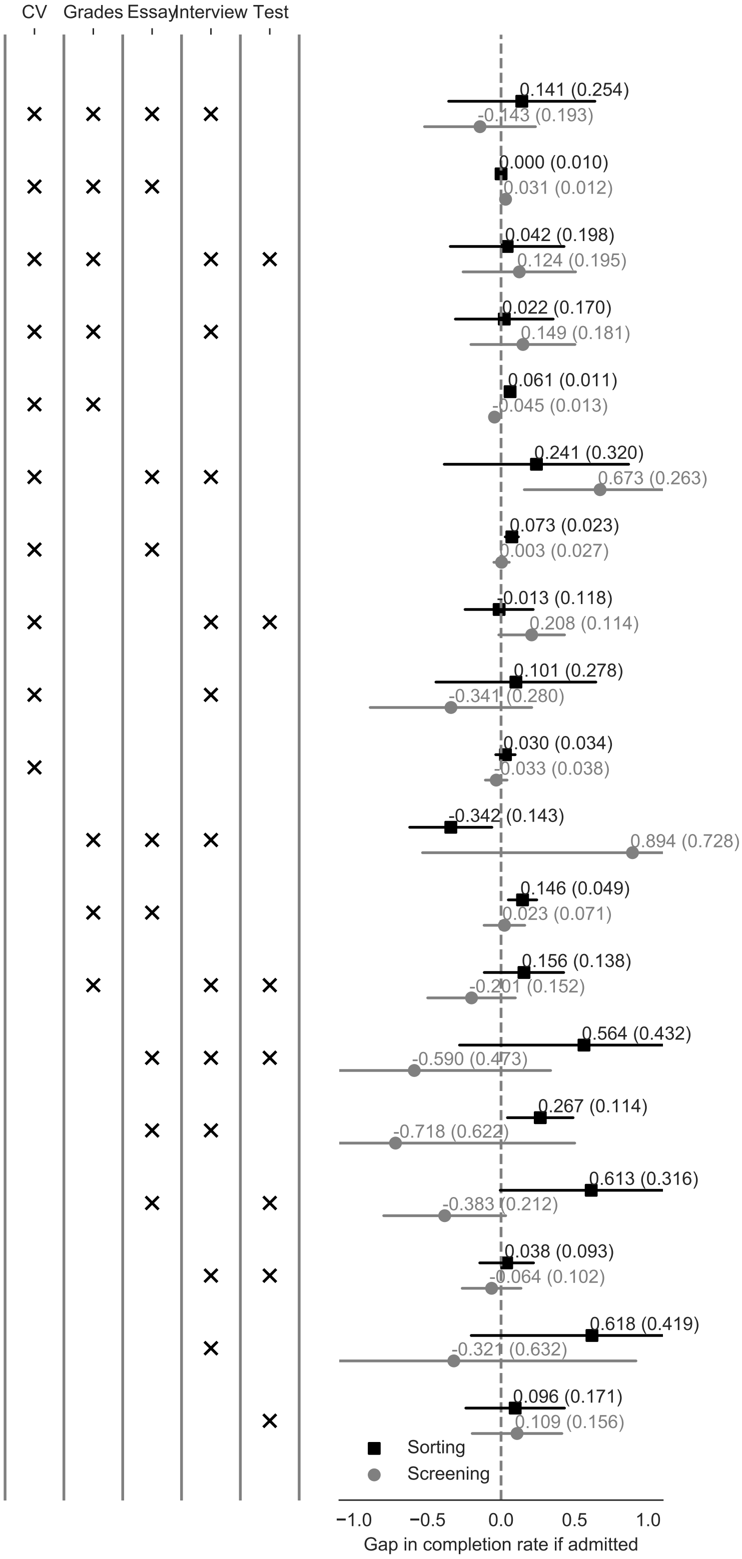


Figure B10: Decomposition, by criteria combination

Note: The figures reproduce results from Table 4 for different subsets of programs. The leftmost figure shows differences between marginal program completion rates between holistic admission (Q2) and GPA-based admission (Q1). The middle figures show the same for overall college completion rates. The right-most figures show value added in terms of college completion rates. Parameter estimates are shown in gray with standard errors in parentheses. Standard errors are clustered on program-year level. Programs use multiple criteria and the sets of programs behind each estimates are overlapping. Appendix Figure

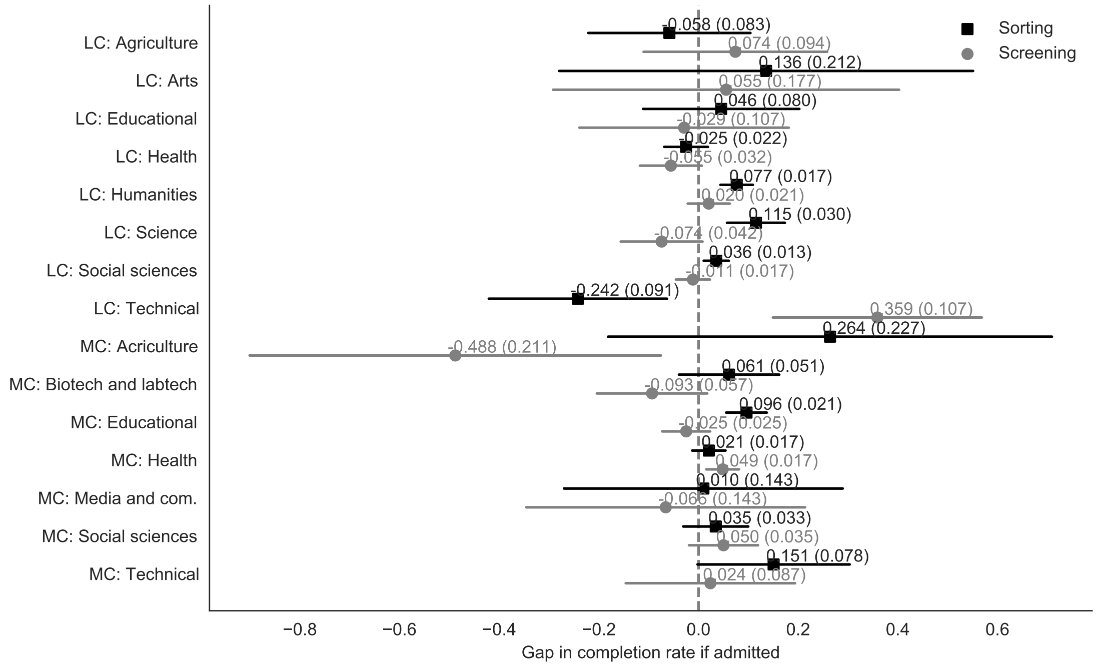


Figure B11: Sorting and screening decomposition of across-quota marginal program completion gap by field

Note: Decomposition estimates of the screening and sorting decomposition in equation (4) for subsets of programs by field.

Table B13: Decomposition of screening and sorting, robustness

Order of poly.	Bandwidth	Slopes	Baseline	Screening	Sorting
1				0.004	0.03
				(0.006)	(0.005)
2			X	0.001	0.033
				(0.008)	(0.007)
3				0.005	0.045
				(0.01)	(0.008)
1	P-Q-Y			-0.007	0.045
				(0.008)	(0.007)
1	P-Q-Y	P-Q		0.002	0.054
				(0.01)	(0.008)

Note: The table shows parameter estimates for standard errors in parenthesis for RDD estimates with varying bandwidth different orders of the polynomials in the running variables. All rows which share values in columns 1-4 are estimated in a stacked design to ensure correct standard errors. The first column show the order of the polynomial use for the spline of the running variable. Specifications denoted by “P-Q-T” in the bandwidth column are estimated using program-quota-year specific optimal bandwidths calculated using RDrobust. Specifications denoted by “P-Q” in the slope column are estimated using program-quota-specific linear splines. The baseline estimates in Table 6 are marked by “X” in the Baseline column. Standard errors are clustered on applicant level.

Table B14: Decomposition of screening and sorting by Quota 2 usage, robustness

				≤.15		(.15,.4]		>.4	
Order of poly.	Bandwidth	Slopes	Baseline	Screening	Sorting	Screening	Sorting	Screening	Sorting
1				-0.051	0.041	0.034	-0.004	0.002	0.042
				(0.012)	(0.008)	(0.011)	(0.01)	(0.011)	(0.011)
2			X	-0.062	0.041	0.027	0.021	0.02	0.034
				(0.015)	(0.01)	(0.014)	(0.012)	(0.014)	(0.013)
3				-0.051	0.061	0.02	0.031	0.036	0.04
				(0.018)	(0.012)	(0.018)	(0.014)	(0.017)	(0.016)
1	P-Q-Y			-0.073	0.069	0.007	0.018	0.014	0.044
				(0.017)	(0.011)	(0.015)	(0.012)	(0.013)	(0.013)
1	P-Q-Y	P-Q		-0.066	0.087	0.025	0.03	0.018	0.037
				(0.023)	(0.014)	(0.019)	(0.014)	(0.016)	(0.015)

Note: The table shows parameter estimates for standard errors in parenthesis for RDD estimates with varying bandwidth different orders of the polynomials in the running variables. All rows which share values in columns 1-4 are estimated in a stacked design to ensure correct standard errors. The first column show the order of the polynomial use for the spline of the running variable. Specifications denoted by "P-Q-T" in the bandwidth column are estimated using program-quota-year specific optimal bandwidths calculated using RDrobust. Specifications denoted by "P-Q" in the slope column are estimated using program-quota-specific linear splines.. The baseline estimates in Table 6 are marked by "X" in the Baseline column. Standard errors are clustered on applicant level.

Table B15: Decomposition of screening and sorting by selectivity, robustness

				Very low		Low		Moderate		High	
Poly.	Bw.	Slopes	Baseline	Screen.	Sort.	Screen.	Sort.	Screen.	Sort.	Screen.	Sort.
1				-0.026	0.01	0.01	0.047	0.034	0.046	0.029	0.005
				(0.025)	(0.021)	(0.01)	(0.01)	(0.01)	(0.009)	(0.017)	(0.013)
2			X	0.012	-0.003	0.023	0.036	0.022	0.07	-0.009	0.026
				(0.035)	(0.027)	(0.014)	(0.012)	(0.013)	(0.011)	(0.021)	(0.015)
3				0.02	0.017	0.027	0.047	0.025	0.082	-0.0	0.029
				(0.045)	(0.032)	(0.018)	(0.015)	(0.017)	(0.013)	(0.026)	(0.018)
1	P-Q-Y			-0.062	0.015	0.01	0.045	0.024	0.063	-0.007	0.01
				(0.033)	(0.028)	(0.013)	(0.012)	(0.013)	(0.011)	(0.027)	(0.017)
1	P-Q-Y	P-Q		0.034	-0.026	0.012	0.043	0.013	0.07	-0.001	0.089
				(0.051)	(0.038)	(0.016)	(0.014)	(0.017)	(0.013)	(0.037)	(0.022)

Note: The table shows parameter estimates for standard errors in parenthesis for RDD estimates with varying bandwidth different orders of the polynomials in the running variables. All rows which share values in columns 1-4 are estimated in a stacked design to ensure correct standard errors. The first column show the order of the polynomial use for the spline of the running variable. Specifications denoted by "P-Q-T" in the bandwidth column are estimated using program-quota-year specific optimal bandwidths calculated using RDrobust. Specifications denoted by "P-Q" in the slope column are estimated using program-quota-specific linear splines. The baseline estimates in Table 6 are marked by "X" in the Baseline column. Standard errors are clustered on applicant level.

Table B16: Decomposition of screening and sorting by criteria, robustness

				CV		Grades		Essay		Interview		Test	
Order of poly.	Bandwidth	Slopes	Baseline	Screening	Sorting	Screening	Sorting	Screening	Sorting	Screening	Sorting	Screening	Sorting
1				0.003	0.026	0.002	0.026	0.03	0.015	0.043	0.06	0.075	0.095
				(0.006)	(0.006)	(0.007)	(0.006)	(0.008)	(0.007)	(0.038)	(0.038)	(0.044)	(0.043)
2			X	0.0	0.027	-0.001	0.027	0.025	0.015	0.042	0.032	0.033	0.137
				(0.008)	(0.007)	(0.009)	(0.007)	(0.011)	(0.009)	(0.05)	(0.047)	(0.054)	(0.051)
3				0.005	0.041	0.005	0.041	0.04	0.031	-0.012	0.089	0.019	0.115
				(0.01)	(0.008)	(0.011)	(0.009)	(0.014)	(0.011)	(0.068)	(0.058)	(0.068)	(0.059)
1	P-Q-Y			-0.006	0.043	-0.006	0.043	0.016	0.038	0.001	0.072	0.063	0.099
				(0.008)	(0.007)	(0.009)	(0.007)	(0.011)	(0.009)	(0.048)	(0.041)	(0.049)	(0.043)
1	P-Q-Y	P-Q		0.003	0.041	-0.0	0.047	0.025	0.04	0.001	0.084	0.024	0.222
				(0.011)	(0.009)	(0.011)	(0.009)	(0.014)	(0.011)	(0.075)	(0.053)	(0.078)	(0.064)

Note: The table shows parameter estimates for standard errors in parenthesis for RDD estimates with varying bandwidth different orders of the polynomials in the running variables. All rows which share values in columns 1-4 are estimated in a stacked design to ensure correct standard errors. The first column show the order of the polynomial use for the spline of the running variable. Specifications denoted by “P-Q-T” in the bandwidth column are estimated using program-quota-year specific optimal bandwidths calculated using RDrobust. Specifications denoted by “P-Q” in the slope column are estimated using program-quota-specific linear splines. The baseline estimates in Table 6 are marked by “X” in the Baseline column. Standard errors are clustered on applicant level.