College admission as a screening and sorting device*

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Abstract

This paper examines how performance-based funding incentives influence college admission decisions in dual-track systems where programs admit students based on either grades or holistic assessment. Using Danish administrative data and regression discontinuity methods, we find that programs respond effectively to funding incentives by equalizing marginal completion rates across admission tracks. A reform removing restrictions on holistic admissions confirms this – previously constrained programs exhibit completion rate gaps across tracks that close once allowed to optimize freely. However, this institutional optimization comes at a broader social cost – rejected holistic applicants are 6.4 percentage points less likely to complete higher education elsewhere. The largest potential social gains from expanding holistic admissions are in selective programs and those currently making least use of this track. The benefits of holistic admissions arise mainly through advantageous self-selection of higher-potential students, with little additional screening benefit.

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

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1 Introduction

The design of college admission systems fundamentally shapes access to higher education and human capital formation in society. A central challenge is how to identify and select students who will succeed in their chosen programs while promoting broader societal goals of educational attainment. Standardized metrics like grades provide clear rankings but may miss important student attributes. Holistic evaluations can consider a broader range of qualities but introduce subjectivity and higher screening costs. Understanding how institutions navigate these trade-offs – and whether their choices align with social objectives – is a necessary prerequisite for designing public policy in education.

We study these questions using Denmark's higher education system, where programs employ two parallel admission tracks: a traditional grade point average (GPA) based admission process, and a holistic evaluation process similar to U.S. college admissions. This dual-track system which admits students in track-specific quotas, combined with comprehensive registry data, provides unique insight into how different admission mechanisms affect both program-specific and system-wide outcomes. Critically, we can observe outcomes for both admitted and rejected applicants across the entire higher education system, allowing us to evaluate efficiency and broader societal implications of different admission strategies.

We make three main contributions. First, we develop a theoretical framework where programs make dual admission decisions to maximize profits. This model generates testable predictions about optimal admission thresholds and helps interpret the efficiency implications of different admission strategies as well as their underlying mechanisms. We then decompose outcomes for marginal admissions into two distinct channels: a sorting channel, where application costs in the holistic track influence applicant pool composition and a screening channel, where holistic evaluation provides additional information beyond GPA.

Second, using regression discontinuity methods, we recover unbiased estimates of counterfactual outcomes that map to the programs' decision margin in the model. We provide evidence that programs equalize marginal completion rates across admission-track specific quotas as predicted by the model, suggesting that the model is a good description of program behavior. In addition we validate our theoretical predictions using a reform in Danish admission regulations. Before our main analysis period, programs faced constraints on holistic admission quotas. Our model predicts that constrained programs would show higher completion rates in holistic quotas than GPA quotas, with these gaps closing when constraints are lifted. The data confirm these predictions: previously constrained programs show large pre-reform gaps that close when they can optimize quota sizes.

We then estimate how programs balance the sorting and screening channels in practice. Our evidence indicates that the benefits of holistic admissions arise primarily through advantageous sorting – higher-potential students are more likely to apply through the holistic track. In contrast, for most programs the additional information gained through holistic screening appears to provide relatively little benefit beyond what is captured by GPA. However, we document that programs with high levels of holistic admission do not reap benefits from sorting but are able to screen applicants effectively. This suggest that programs adapt their admission procedures to the applicant pools they face.

Third, we demonstrate that program-optimal admission decisions may diverge meaningfully from socially optimal outcomes. While marginal admits have similar completion rates across quotas, rejected marginal applicants from the holistic quota are 6 percentage points less likely to complete higher education elsewhere compared to their GPA-quota counterparts. This difference reveals that while programs optimize their own completion rates effectively, this institutional optimization may come at the cost of system-wide college completion, as programs do not fully internalize the outcomes of students they reject who could succeed elsewhere in the system. Reallocating admission slots toward holistic evaluation could therefore increase system-wide college completion. We show that this is particularly the case for highly selective programs and programs admitting few applicants through the holistic quota.

To assess equity issues, we characterize the applicants at the margin in the two types of quotas. While marginal holistic applicants have mechanically lower grades, they are remarkably similar to other applicants, with a slight over-representation of ethnic Danes and males. We therefore conclude that marginal changes in admission modes likely have little effect on the pool of admitted applicants.

Our paper advances four related literatures. First, we contribute to research on admission mechanisms and screening technologies. While numerous studies examine the predictive power of standardized tests (Burton and Ramist, 2001; Zwick, 2007), less attention has been paid to how different screening technologies interact. Some work shows that selective use of test components can improve prediction (Bettinger, Evans, and Pope, 2013; Silva, 2022; Bjerre-Nielsen and Chrisander, 2022), and studies of subjective admission instruments generally find modest incremental value beyond standardized measures (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). However, as Rothstein (2004) notes, most studies face significant selection challenges by observing outcomes only for admitted students. Our setting overcomes these limitations by providing system-wide data on both admitted and rejected applicants.

Second, we enhance understanding of how admission mechanisms affect applicant behavior and sorting and how programs can incentivize sorting. Research shows that application requirements and costs significantly influence college choice patterns. Smith, Hurwitz, and Howell (2015) find that essay requirements and fees reduce applications without improving match quality, while Pallais (2015) demonstrates that even small cost changes substantially affect application decisions. Studies of mandatory entrance exams (Hyman, 2017; Hurwitz, Smith, Niu, and Howell, 2015) further highlight how admission policies shape applicant pools. Dynarski, Nurshatayeva, Page, and Scott-Clayton (2023) provides a recent overview of the literature on non-pecuniary application costs. Most closely related are Friedrich, Hackmann, Kapor, Moroni, and Nandrup (2024), who study how medical schools in Denmark respond strategically to information held by rival programs and students. They find that programs exhibit "home bias" in admissions partly to mitigate the risk of admitting students rejected by their preferred programs, though their focus is on interdependent values rather than the screening versus sorting trade-off we analyze. Avery and Levin (2010) provide related evidence that early admission programs allow students to signal their fit for a particular college, while Lee (2009) argues that screening on preferences helps programs reduce the risk of admitting students rejected elsewhere.

Third, we connect to broader work on allocation mechanisms and match quality in higher education. While much research focuses on college selectivity and affirmative action effects (Arcidiacono, Lovenheim, and Zhu, 2015; Arcidiacono and Lovenheim, 2016; Bleemer, 2022), we show how admission mechanisms themselves affect match quality. As Dillon and Smith (2020) note, evidence for academic ability-based match effects is mixed. Our results reveal that match effects operate through additional channels, particularly the interaction between screening technologies and applicant self-selection.

Lastly, our paper relates more broadly to the interpretation of educational returns estimated using regression discontinuity designs. Studies that estimate individual returns (f.e. Öckert (2001, 2010); Hastings, Neilson, and Zimmerman (2013); Kirkeboen, Leuven, and Mogstad (2016)) can inform demand side decisions for marginal applicants. However, we demonstrate that program-specific cutoffs are products of institutional optimization based on potential outcomes of applicants. As a consequence, cutoffs are endogenously determined, and while this may not threaten the internal validity of locally estimated returns for applicants, it poses substantial challenges for interpreting differences within or across programs or institutions in terms of their supply side policy implications.

Our findings have implications for education policy. While programs appear adept at optimizing their own outcomes through admission decisions, this optimization may not maximize societal returns to public provision of education. The substantial wedge between program-specific and system-wide outcomes suggests potential benefits from policies that encourage programs to consider broader effects, perhaps through modified incentive structures or admission regulations. However, implementing such policies requires careful attention to measurement challenges, as system-wide effects are inherently more difficult to quantify than program-specific outcomes.

The paper proceeds as follows. Section 2 details the institutional context. Section 3 presents our theoretical framework and develops testable predictions. Section 4 presents our empirical research design and we describe our data in Section 5. Section 6 through 8 present our empirical results, and section 9 concludes with policy implications.

2 Institutional background

Danish higher education is essentially a public system that is accessible to everyone with a diploma from the academic high school track ("Gymnasiale uddannelser”). There are 8 universities and 7 university colleges distributed across 38 locations, along with 8 business academies, each with multiple campuses. At entry, higher education provides 3-year bachelor programs and 2- to 4-year professional degrees, with over 90% of bachelor degree graduates subsequently completing a master’s degree. Programs are defined as a specific field of study at a given institution. Higher education institutions do not charge tuition fees, and students can use a generous public grant and loan system to cover living expenses during their studies.

Programs and assessment The Danish funding model combines fixed grants with performance-based subsidies. The majority of program funding is based on course work completion. In addition, performance incentives are tied to completion times. This funding model 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 are evaluated in their main admissions, which

[1]A few programs are restricted from increasing capacity, either because of high unemployment rates of graduates or because of the government being a monopsonist employer. Among the former are some humanities programs and among the latter are medical doctors.

we refer to as Quota 1 (Q1), where programs exclusively use average high-school GPA to rank applicants. High-school GPA is based on a combination of central and externally graded exit exams and continuous assessment.[2] In Quota 2 (Q2) applicants are ranked based on holistic evaluations of their applications. Applicants need to specifically apply for assessment in Quota 2. Both quotas admit students to the same program.[3]

In our main sampling window, 2012-2015, programs were free to choose the share of applicants that they wished to admit through these holistic admissions. Before 2012, academic programs were restricted to accepting no more than ten percent in Quota 2. We exploit this policy variation in Section 6.4.

Programs must evaluate and rank all applicants to Quota 2 regardless of the quota size. Only applications directed to the program are observed by the assessment committee of a program, and the program does not know its priority on the applicant's rank-ordered list. In the period we investigate, the individual programs rank applicants in Quota 2 internally, and the process was not standardized.

Programs can partly choose the evaluation instruments in Quota 2 and combine them as they see fit. Instruments can be "objective", for example, a subset of high school grades (grades) or college entrance tests (tests). Instruments may also be "subjective" and may for example involve the evaluation of relevant experience (CV), written assignments (Essay), or interviews (Interview). We employ the classification developed by UFM (2020). Appendix Figure B1 documents that CV, grades and essays are the most popular instruments and programs typically use two or three instruments.

The evaluation instruments of a program are known to the applicant at the moment of application, but the actual scoring is not and anecdotal evidence suggests that the scoring is informal in the assessment committees. From the perspective of the applicant, the evaluation of applicants in the holistic admission 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 investigate these rankings, and programs in this period most likely treated them as private information.

Applications and offers Applications are submitted through a single online portal that is managed by a government agency. There are no application fees, and applicants can apply to up to eight programs and must rank these programs from most to least

[2]GPA is a number on a 7 point scale that is recorded up to 1 decimal place. A lottery number is used to break ties on the first decimal.

[3]These quotas were originally implemented when centralized admission was introduced in 1977 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**	**Quota 2**	**Rank**	**Program**	**Priority**
1	Econ - Aarhus	✓	1	Econ - Aarhus	GPA
2	Econ - Copenhagen		2	Econ - Aarhus	Quota 2 ranking
3	Business - Aarhus		3	Econ - Copenhagen	GPA
			4	Business - Aarhus	GPA

Note: The table illustrates how Quota 2 is handled in the Deferred Acceptance procedure. The left panel is an example of how the application list looks to the applicant. The right panel shows how the centralized system embeds the Quota 2 application below the Quota 1 application.

preferred.[4] Applicants who only apply to programs' main GPA-based admissions in Quota 1 must submit their applications before mid-July after the final high-school GPA is known. The program application deadline for applicants who also want to be considered in Quota 2 is in March. The earlier deadline allows programs to assess and rank all their Quota 2 applicants. After the deadline for Quota 1 in July, the programs report their ranking of applicants within each quota to the Ministry of Higher Education.

The ministry computes admission offers based on applicants rank-ordered lists, programs' quota-specific capacity and rankings of applicants using a Deferred Acceptance algorithm with multiple tie-breaking (DA, Abdulkadiroğlu and Sönmez (2003)). The admission algorithm first unrolls the application lists into a rank-ordered list where, for every applicant, all Quota 2 applications to a program are ranked after the default (Quota 1) application to that program but before the next-ranked program. Table 1 illustrates how this works in practice.

The DA mechanism results in an allocation which can be represented in terms of quota-specific cutoffs where applicants get their highest ranked program-quota in which their eligibility score is above the cutoff (Azevedo and Leshno, 2016). With the expanded rank-ordered list, an applicant is first admitted in Quota 1 if she clears the cutoff. If she does not clear the Quota 1 cutoff she can be admitted in Quota 2 if she clears that cutoff (given that she applied to Quota 2). If not admitted to the program in either Quota 1 or 2 the applicants is assessed in the next program on her rank-ordered list.

The presence of the Quota 2 option does not change the strategy-proof nature of the admission process (over and above the limit of 8 programs).[5] Moreover, the presence

[4] Although the maximum of eight may seem limited, 75 percent of the applicants do not apply to more than three programs, less than 10 percent apply to more than five programs, and only 3 percent of the applicants exhaust the list which puts an upper bound on the number of people that are constrained (probably in the neighborhood of 2 percent).

[5] Without Quota 2 all programs would use the same priority score and the DA mechanism would there-

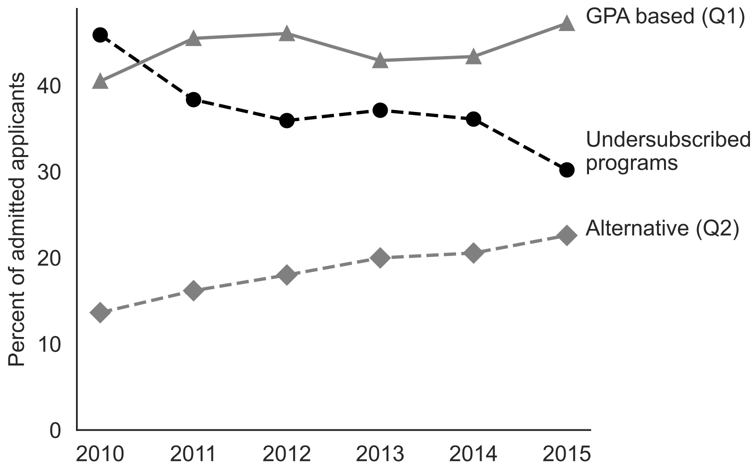


Figure 1: Admitted applicants by admission channel

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

of Quota 2 does not affect the counterfactual program either. While the DA algorithm computes offers sequentially, the admission process is not sequential for applicants, and everybody receives admission offers for programs (and not quotas) at the same time in August, regardless of whether they applied or were admitted through Quota 2.

On the day the offers are sent out, the number of applicants admitted and rejected through each quota is made public on the website of the Ministry of Higher Education. The Quota 1 cut-offs in terms of GPA are made publicly available on a governmental website and treated as front-page news. The scoring of applicants (and hence cut-offs) in Quota 2 is not public, though we observe it in our data.

Figure 1 shows how the share of applicants who are admitted through Quota 1, Quota 2 and to non-oversubscribed programs developed during our period of analysis. Over 40 percent of the admitted applicants are admitted based on GPA (Quota 1), while the share admitted through holistic quotas (Quota 2) has been increasing from 14 to 25 percent. This reflects stronger competition, as the share admitted to programs that are not oversubscribed has been steadily declining.[6]

fore be serial dictatorship. Bjerre-Nielsen and Chrisander (2022) show theoretically that the strategy-proofness of the DA mechanism is maintained in the Danish setup abstracting from truncation of rank-ordered lists.

[6]Note that while Figure 1 reports shares of admitted applicants, our analysis is at the program application level.

3 Theoretical framework

In this section, we model the decision problem of the program admission officer. We assume that the program seeks to maximize profits. In addition, we assume that the content and standards of the program do not depend on the program's admission decisions, which implies that applicants' potential outcomes conditional on admission can be taken as given. We analyze the unconstrained problem and the case where the program faces a relative size constraint with respect to the holistic admissions.

Optimal admission policy We normalize the mass of applicants to size 1 without loss of generality. For now, all applicants are assumed to apply to Quota 2 and we relax this assumption below. The program observes two signals of applicants' quality y^1. In Quota 1, they observe the applicants' (ranked) GPA, r_1, and in Quota 2, the information generated by the holistic assessment, which is summarized by their rank in Quota 2, r_2.

In line with how the offers are generated by the DA, an applicant is admitted if she either clears the Quota 1 cutoff a or Quota 2 cutoff b:

$$A = \begin{cases} 1 & \text{if } r_1 \geq a \vee r_2 \geq b \\ 0 & \text{otherwise} \end{cases}$$

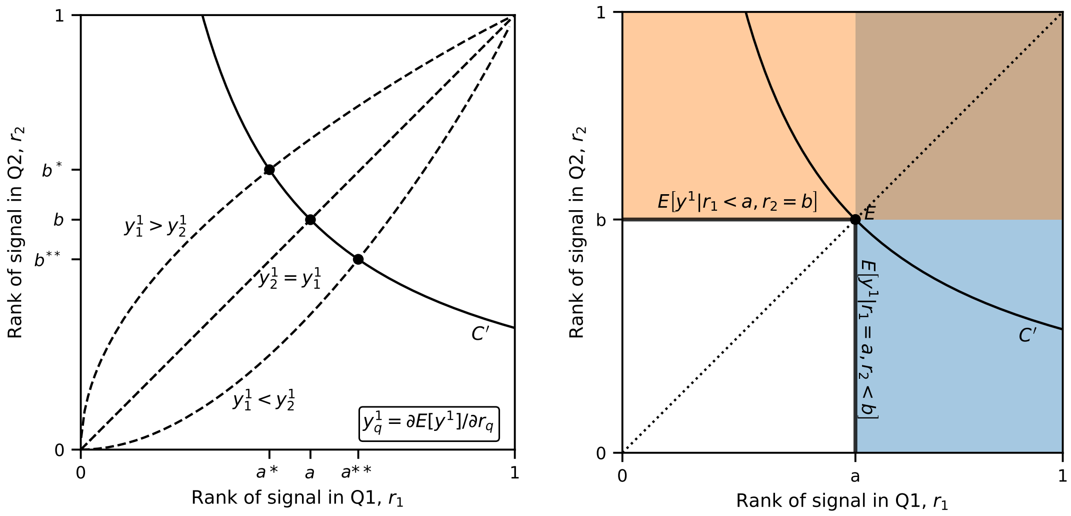
The program chooses the size of Quota 1 and Quota 2 in program admissions that maximizes the ex-ante expected program completion rate of the admitted students net of the cost of admission. There is a one-to-one mapping between capacity and the cutoffs, and we model the program as setting the latter. This gives the following objective function

$$\max_{a,b} E(y^1 \mid A = 1)\Pr(A = 1) - C(\Pr(A = 1)) \tag{1}$$

where y^1 is the potential program completion rate conditional on admission $A = 1$.[7] The expectation and probabilities in the program's objective function (1) are with respect to the joint distribution of r_1 and r_2 in the population of the program's applicants, and we assume that the expectation of y^1 is convex in r_1 and r_2. Finally, it is assumed that the admission cost function $C(\cdot)$ increases in the share of admissions ($C' > 0$).

Appendix A derives the first-order conditions of the program's optimization problem in (1) which show that in an interior solution the program will equalize the marginal

[7] The supersetting of y^1 anticipates our potential outcomes framework in the empirical section.



(a) Screening technology

(b) Comparison at the margin

Figure 2: Optimal admission policies

Note: The figures show a simulated example for an interior solution of the programs maximization problem where applicants are admitted both through the GPA-bases quota (Quota 1) and the holistic quota (Quota 2). The dotted lines in Figure 2a show the cutoffs that equalize marginal completion rates for three different signaling technologies in Quota 2 relative to Quota 1. The cutoffs are set by equating marginal completion rates to the marginal cost of admission which happens at the intersection with the solid line. Figure 2b shows the location of the admitted applicants in the shaded area. The solid thick lines show the location of the quota-specific marginal applicants. The model and extensions are presented in Appendix A.2.

completion rate across the two quotas:

$$E(y^1 \mid r_1 = a, r_2 < b) = E(y^1 \mid r_1 < a, r_2 = b) = C', \tag{2}$$

where the first term is the completion rate for applicants who are marginally admitted based on GPA, the second term is the completion rate for the applicants at the holistic admission margin, and the final term is the marginal cost of admission.

The intuition is illustrated in Figure 2 for a numerical example that is outlined in detail in Appendix A.2. The diagonal dashed line shows all application cutoffs that equalize completion rates of marginal applicants in both quotas, i.e. the left equality in (2) when signals are equally informative about the potential completion rate in Quota 1 and Quota 2. The solid line is the marginal cost, which is a function of the share of admitted applicants. The intersection of the marginal cost function and the envelope that equalizes completion rates at the margin across quotas denotes the program's optimal admission policy at (a,b). This equilibrium is shown in panel (b) of Figure 2, where the optimal location of the cutoff is denoted by E. The location of marginal applicants whose expected completion rates are equated is shown in solid straight lines going left and down from E.

If the signal observed in Quota 2 is noisier, i.e. $\partial E[y^1]/\partial r_1 > \partial E[y^1]/\partial r_2$, then the program decreases the admission cutoff in Quota 1 and increases the admission cutoff in Quota 2 (shown in the figure as a^* and b^* respectively), which means that more students are admitted based on GPA and fewer students are admitted based on holistic assessment. In the limiting case where r_2 is uninformative ($\partial E[y^1]/\partial r_2 = 0$), no one is admitted through holistic assessment and admissions are purely based on GPA. The reverse also holds; when r_1 becomes less informative than r_2, then more applicants are admitted through holistic admissions, and in the limiting case, when r_1 becomes uninformative ($\partial E[y^1]/\partial r_1 = 0$), we end up in a pure holistic regime. In this simple setup, holistic admissions can therefore provide additional information for a given pool of applications, and if this information is predictive of outcomes, the program can improve its output. We refer to this mechanism as screening.

Inelastic Quota 2 applications In practice, not everybody applies to Quota 2. In this case, we model the objective function of the program as follows:

$$\begin{aligned}\max_{a,b} E(y^1 \mid A=1, Q2=1)\Pr(A=1 \mid Q2=1)\Pr(Q2=1) \\ +E(y^1 \mid A=1, Q2=0)\Pr(A=1 \mid Q2=0)\Pr(Q2=0) \\ -SC(PR(Q2)) - C(\Pr(A=1)),\end{aligned}$$

where SC is a convex screening cost which is a function of the total share applying to Quota 2, which mirrors our institutional setup. $C(\cdot)$ is the admission cost as above.

It can be shown (see Appendix A.1) that if Q2 applications are inelastic with respect to a and b, then the basic intuition from above is preserved. Admission cutoffs are again set such that the expected completion rates for marginal applicants equal the marginal cost of admission. Let ω be the share of applicants that applied to the holistic admissions ($Q_2 = 1$) who are at the GPA-based admission margin ($r_1 = a$), the equalizing completion rates at the two admission margins then becomes:

$$\begin{aligned}\omega E(y^1 \mid r_2 < b, r_1 = a, Q2 = 1) + (1-\omega)E(y^1 \mid r_1 = a, Q2 = 0) \\ = E(y^1 \mid r_1 < a, r_2 = b, Q2 = 1) = C' \quad (3)\end{aligned}$$

where the term to the left-hand side of the first equality corresponds to the expected completion rate for marginal applicants for GPA-based admissions ($r_1 = a$). This group consists of applicants who did not apply to the holistic admissions ($Q_2 = 0$) and those who did ($Q2 = 1$) but are not admitted there ($r_2 < b$). The term on the right-hand side of the first equality is the expected completion rate for holistic-admission applicants at the margin of these holistic admissions ($r_2 = b$), and who do not qualify based on their GPA ($r_1 < a$). Finally, marginal completion rates should equal marginal admission costs C'.

The applicants in Quota 2 are now potentially different from the overall pool of applicants to the program. If the selection into holistic admissions is positive then this provides an additional benefit to the program because it can now admit applicants who do better in expectation. We refer to this channel as sorting. The overall benefits of holistic admissions therefore come from the screening motive mentioned above, and this additional sorting channel. In Section 8 we quantify the relative importance of these two mechanisms.

Constraining holistic admissions Next, we consider what happens when the relative size of holistic admissions is capped. This case is discussed in Appendix Section A.1, and illustrated for our numerical example in Figure 3 where the screening technology in the two quotas are equally predictive. The dashed line traces all admission cutoffs a and b where admissions through holistic evaluations are restricted to a fixed share of total admissions. All a and b above this line are feasible in the sense that the share of holistic admissions in these cases does not exceed the cap. Instead of moving down the solid black line, we now move down the outer envelope of the solid black line and the dashed black line until it crosses the marginal cost function. In the figure, the share is chosen so that it is binding given the marginal cost of admission C'. Relative to the program optimal solution, E, the cutoffs are now set at E'.

The model predicts that when programs are constrained in setting the size of holistic admissions they will set the cutoffs $b' > b$ and $a' < a$. As the expected completion rate is increasing in both r_1 and r_2 this implies that the marginal applicant in holistic admissions outperforms the marginal applicant in the GPA-based quota. In Section 6.4 we confront this prediction with the data when we study a reform that relaxed a binding ten percent cap on the relative size of Quota 2 admissions.

Elastic Quota 2 applications When we extend the model to allow for endogenous sorting into Quota 2 application, we find that programs can no longer reason at the admission margin alone.

An applicant will apply to Quota 2 if the expected utility applying to Quota 2, i.e. admission through Quota 2, outweighs the application cost. If we normalize applicants' utility of admission to 1, then an applicant's expected utility equals her expected prob-

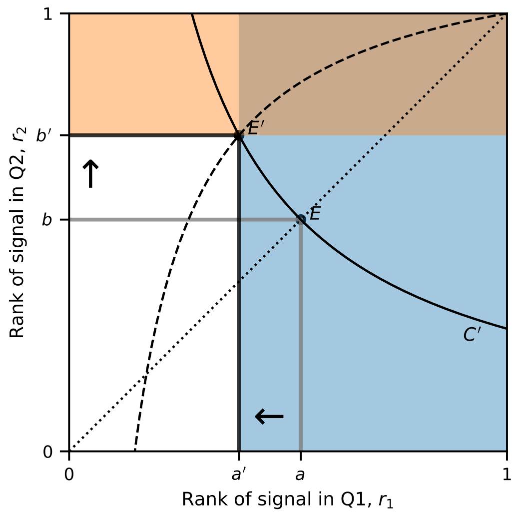


Figure 3: Optimal admission policy with a binding relative size constraint

Note: The figure shows the effect of imposing a maximum on the share admitted through the holistic admission channel, Quota 2. This restriction is illustrated by the dashed line. The constrained optimum is now E', with accompanying cutoffs a' and b'. See Figure 2 for further details.

ability of not being admitted in Quota 1 while being admitted in Quota 2. We allow the application cost AC to be a function of applicant quality, y^1 and the instruments I that the program uses to assess the applicants in the holistic admissions. The application decision then becomes the following:

$$\Pr(r_1 < \hat{a} \wedge r_2 \geq \hat{b} \mid y^1, I) > AC(y^1, I), \tag{4}$$

where $\hat{a}$ and $\hat{b}$ are the applicants expectations of the cutoffs set in Quota 1 and 2 respectively.

Equation (4) highlights two mechanisms that affect sorting into the Quota 2 application pool: the expected cutoffs and the screening technology. Cutoffs matter because applicants respond to admission probabilities. If the probability of admission through Quota 1 increases (lower $\hat{a}$), applicants are less likely to enter into the Quota 2 pool, because they pay a cost to do so. Likewise, if the probability of admission in Quota 2 increases (lower $\hat{b}$) entering the pool becomes more attractive.[8] Because signals are noisy, applicants face uncertainty even when cutoffs are known. As all applicants have

[8] In the notation above r_2 is the rank in Quota 2. Strictly speaking, as the composition of a pool changes, so does the rank and applicants would need to internalize application behavior of other applicants. To circumvent this complication, the cutoffs are defined in the signal space in the model in Appendix A. To avoid complicating the notation in the main text we abstract from this modification in (4).

a non-zero probability of being affected by a change in cutoffs the choice of cutoffs therefore affects both the size and the composition of the Quota 2 applicant pool.

The screening technology I enters (4) in two distinct ways. First it affects the precision and possible bias of the signal sent in Quota 2 and thus the probability of admission. Applicants of different quality may therefore face different levels of uncertainty depending on the instruments used by the program. Second, the assessment instruments also affect individuals' application costs. Not only will some instruments (f.e. interviews or test taking) require more time and effort of the applicants than others (f.e. use of specific grades or CVs), but these costs may also correlate with applicant quality. Heterogeneous applications cost is therefore another potential additional channel that can create sorting into Quota 2.

We introduce elastic Q2 applications by incorporating equation (4) into our stylized model above. We assume that applicants have rational expectations about cutoffs, and that the program understands how the choice of cutoffs and assessment instruments influence the composition and mass of the Quota 2 applicant pool. Appendix A details the full model and provides numerical solutions.

We show that with endogenous applications and uniformly distributed random application costs, the first-order condition in (3) no longer holds. To see this, start at a point where marginal completion rates are equalized. By slightly relaxing the Quota 2 cutoff, more applicants enter the pool, potentially increasing the mass of high-quality applicants above the cutoff. This potential inframarginal benefit may offset losses at the margin, where completion rates are no longer equalized and the marginal Quota 2 applicant underperforms the marginal Quota 1 applicant due to the lower Quota 2 cutoff. When we introduce screening costs into this scenario, a large applicant pool becomes costly for the program. Consequently, the program raises the Quota 2 cutoff to deter applicants from entering the pool. Screening costs introduce a positive wedge between marginal Quota 2 and Quota 1 applicants, and this mechanism therefore reverses the performance gap, causing the marginal Quota 2 applicant to outperform the marginal Quota 1 applicant. Thus, observing a higher-performing marginal Quota 2 applicant is consistent with a model with endogenous applications and screening costs.

In Appendix A we also investigate the second channel for selection by introducing correlation between application costs applicant quality. If application costs tend to be smaller for high-quality applicants, programs can lower standards in Quota 2.

Additional objectives in college admissions The behavioral model in this section assumes that programs maximize program completion net of costs. We argued that this is reasonable given the institutional details and funding structure in Denmark, and find below that on average it is a good description of the data. While the model may be a good approximation of the behavior of a typical program, some programs may have additional objectives. One important case is when programs value other characteristics of applicants such as their gender or race. In this situation we would no longer expect (3) to hold. More specifically, this will lead programs to trade-off completion for other attributes of applicants and drive a wedge between the marginal completion rates across quotas (Bhattacharya, Kanaya, and Stevens, 2017). Any violation of (3) can therefore also be interpreted as a sign of programs having non-academic objectives in addition to reaping inframarginal gains from endogenous sorting. The marginal gap that would ensue depends on the correlation between the characteristics that the program values and the potential completion rate of the applicant. If the program wants to admit applicants from specific groups that would not make the cut based on their academic credentials then this correlation is negative, and we should expect a negative gap, i.e. marginal Quota 2 applicants being outperformed by marginal Quota 1 applicants. The characterization of marginal applicants in Section 6.5 suggests that this is not a good description of average program behavior.

4 Empirical approach

4.1 Recovering potential outcomes at the admission margin

The Deferred Acceptance admission mechanism described in Section 2 results in admission for applicants who are ranked high enough, while applicants with marginally lower rankings are rejected. This setup gives rise to a fairly standard regression discontinuity design, where the application cutoff is defined by the application score of the last admitted student and has been used extensively to study the impact of college on individual outcomes (Öckert, 2001, 2010; Kirkeboen, Leuven, and Mogstad, 2016; Heinesen, Hvid, Kirkebøen, Leuven, and Mogstad, Forthcomming).

To understand how the application cutoffs arise, first note that programs rank applicants in all quotas where the applicant is eligible. For the default Quota 1, all applicants are ranked based on their GPA. Applicants who also applied for admissions based on holistic evaluations are ranked based on alternative criteria. For any program p in year t, the number of applicants that are admitted through Quota 1 is limited by programs' capacity and, if over-subscribed, the rank of the last admitted applicant defines the admission cutoff c_{1pt}. Applicants whose ranking in Quota 1 is below c_{1pt} but who applied for holistic evaluation are considered in the same manner, but this time based on their ranking using the alternative criteria within Quota 2. This again implicitly defines an application cutoff which is c_{2pt}, the rank of the last admitted applicant in Quota 2, and applicants that reach this cutoff are admitted in Quota 2. Applicants only receive an offer above the cutoff if they are not admitted to a higher ranked program on their application list.

We exploit the fuzzy RD design generated by this admission process to estimate the program completion rates of the marginal applicants in equation (3). In contrast to much of the literature that exploits similar designs, the focus here is on the program as a decision maker. This implies that the unit of analysis must be the application and not the individual applicant, as they can apply to more than one program. We therefore retain all applications in the data and use 2SLS to estimate the expected potential outcomes given admission for the marginal applicant who gets admitted to the program if ranked just above the cutoff, but not if ranked just below.

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

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

The subscripts highlight that the data is at the application level, where we observe whether individual i applied to program p and quota q in year t. The key variable of interest A_{ipt} is a binary variable that equals one if applicant i received an admission offer for program p in year t and is zero otherwise. Note that program admission A_{ipt}, in line with what happens in practice, is not quota specific.

We estimate (5) separately for each quota and define the Quota q assignment variable r_{qipt} as the percentile distance of applicant i's application score from the admission cutoff. More specifically, because programs are trading off admission decisions at the margin, we ensure that the ranking scale is comparable across quotas and define r_{qipt} as 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 Quota 1 applicants (in the given program-year combination).

To account for nonlinearities in the running variable, the specification in (5) includes a quadratic spline with a knot at zero, which we denote by $B_q(r_{qipt})$.[9] Finally, 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}).

The prediction of the theoretical framework above is in terms of performance in the program. We therefore need to estimate counterfactual program completion *levels*,

[9] In order not to exhaust the Greek alphabet we use the generic notation $B_q(r_{qipt})$ and FE_{qpt} throughout with the understanding that these are allowed to vary across specifications.

Y^1_{ipt}, of marginal applicants rather than *effects* of admission on program completion. To estimate this, we specify the dependent variable as $A_{ipt}Y_{ipt}$, see f.e. Abadie (2003). To quantify potential externalities of program admission, we estimate the value added (i.e. effect) of admission on completing any program, that is, college completion. To do this, we change the dependent variable in equation (5) to $Y_{college,ipt}$, which in this case is an indicator for college completion rather than program completion. This specification recovers an estimate of college completion value added, $Y^1_{college,ipt} - Y^0_{college,ipt}$.

Estimation in the application level data means that there is mechanical fuzziness in program admissions. To take this into account, we instrument for A_{ipt} with cutoff crossing $z_{qipt} \equiv [r_{qipt} \geq 0]$ in the following first stage:[10]

$$E[A_{ipt} \mid z_{qipt}, r_{qipt}, FE_{qpt}] = \pi_q \cdot z_{qipt} + B_q(r_{qipt}) + FE_{qpt}.$$

We estimate (5) using 2SLS separately for the GPA-based admission margin and the holistic admission margin. As outcomes, we consider both program completion Y^1, college completion Y^1, as well as value added $Y^1 - Y^0$ for college completion. We cluster standard errors at the program-year level.[11]

While our main estimation results are based on the 2SLS estimation framework above, we validate this approach in several ways. We estimate non-parametric cutoff crossing effects on the sample of applications using the following specification:

$$E[W_{ipt} \mid z_{qipt}, r_{qipt}, FE_{qpt}] = \delta_q z_{qipt} + f_q(r_{qipt}) \tag{6}$$

where W_{ipqt} can be i) program admission A_{ipt}, ii) program completion Y_{ipt}, or iii) college completion $Y_{\text{college},ipt}$. The running variable is accounted for through $f_q(r_{qipt})$ which is estimated non-parametrically on both sides of the admission cutoffs using local linear regression. Most applicants apply to multiple programs, and we estimate equation (6) at the application level using the implementation and default bandwidths of Calonico, Cattaneo, Farrell, and Titiunik (2017) and apply their method for rescaling reduced forms to compute the IV estimate. Standard errors are bootstrapped with 200 repetitions. To compare the nonparametric implementation with our 2SLS specification, we perform the 2SLS estimation within the same bootstrap samples. We perform and report the results from analyses that investigate the robustness of the empirical implementation

[10] For applicants with the same GPA, the ranking is determined by a lottery. We therefore define the instrument as $z_{1ipt} = A_{ipt}$ for Quota 1 applicants exactly at the cutoff.

[11] Standard errors on the completion gap across quotas are obtained by stacking the Quota 1 and Quota 2 data and clustering across program-years.

outlined here in section 6.3 below.

5 Data

The starting point of our analysis is the application data for the years 2010–15 which provides us with information on applicants' preference lists, the ranking of the applicants in Quota 1 and Quota 2 (if applicable), and program offers. We link this information on individuals' applications to registry data from Statistics Denmark which contain information on individuals' educational trajectories and outcomes, as well as gender, age, and family background; in particular parental income, education, and immigrant status. We focus on regular college applicants and therefore exclude Quota 2 applicants who do not have a GPA and therefore do not compete in Quota 1.[12] In addition, we exclude applicants over 30 years of age. We restrict our analysis to people who apply to at least one restricted program. We scale variables in percentiles before the sample exclusions, which means that it is relative to all applicants in a given year.

In our main analysis, we focus on the period from 2012 to 2015 when there were no restrictions on the share of applicants that the programs could admit using holistic assessment. When we turn to the analysis of the reform, we extend our data backward to 2010, thus including two more years.

Table 2 reports descriptive statistics for our main sample in columns 1 and 2 and for our additional sample in columns 3 and 4. The first column reports the averages for all the applications (which are all evaluated in the GPA-based quota). We observe about 179 thousand people applying to higher education in the main period we study, who together submit nearly 400 thousand program applications. More than 60 percent of the applications are from female applicants, and 14 percent are from applicants with an immigrant background. The parent income rank is, on average, at the 72nd percentile (SES), reflecting the higher likelihood of attending tertiary education for high-SES individuals.[13] The applications are, on average, from slightly positively selected applicants measured by high-school GPA.

About 40 percent of the applications are also evaluated in the holistic quota. The second column shows that Quota 2 applications are more likely to be from female applicants, slightly older applicants, and from applicants with non-immigrant backgrounds. They are similar in SES but have substantially lower ability as measured by GPA. The

[12]Under 800 applicants have a GPA in the Danish registers but do not compete in Quota 1.

[13]We do not observe parental income for 1.2 percent of the sample and exclude these observations in the computation of the average income rank.

Table 2: Descriptive statistics for analysis samples

	Main sample (2012-2015)		Additional sample (2010-2011)	
	Full (1)	Q2 (2)	Full (3)	Q2 (4)
Female	0.63	0.64	0.62	0.63
Age	21.7	22.2	21.5	22.2
Immigrant	0.13	0.10	0.11	0.08
Parental income rank	0.72	0.73	0.75	0.76
High school GPA rank	0.52	0.43	0.57	0.49
Apply in Q2	0.40	1	0.35	1
Admitted	0.27	0.26	0.31	0.29
Completes program (given admission)	0.49	0.51	0.59	0.60
Completes in time (given admission)	0.47	0.49	0.56	0.57
Completes college (given admission)	0.82	0.82	0.84	0.83
Applications	399,654	158,223	202,491	71,661
Applicants	178,774	75,505	105,646	39,655

Note: The table shows descriptive statistics for our two samples. The unit of observation is an application. The sample for the holistic assessment in column 2 is a subset of the sample in column 1, and column 4 is a subset of column 3. We do not observe parental income for 1.2 percent of the sample and exclude these observations from the computation of average parental income rank.

latter finding is intuitive, as applicants with higher GPAs are more likely to be admitted through the regular Quota 2 admissions and, therefore, are less likely to apply for holistic assessment in Quota 2. In terms of outcomes, the two samples are similar. Around 27 percent of applications lead to an offer of admission. Completion rates are measured 5 years after applying to a program. Conditional on admission, the program completion rate is about 0.5, and on-time completion is 0.47, which means that the overwhelming majority of applicants who complete a program do so on time. While it is common for students to drop out from a program, for almost 80 percent of applications, we observe a completed program after 5 years, which indicates that relatively few applicants end up having no higher education.

Columns 3 and 4 present the same statistics for the sample, which we use to measure the impact of lifting the restriction on Quota 2 size. Again, we observe that the sample of applications in holistic assessment is similar to the overall sample, except for a lower GPA. We stress that overall average characteristics do not necessarily coincide with the characteristics of applicants and applications at the margin of admission. We return to this point in Section 6.5 where we estimate the characteristics of the marginal applicants in the two types of admission quota.

Table 3: Bunching and balancing around the admission cutoffs

	Covariate imbalance (s.e.)					Density [p-val]
	Female (1)	Immigrant (2)	Income (3)	Apply to Q2 (4)	GPA rank (5)	Disc. (%) (6)
GPA-based (Q1)	0.007	-0.002	0.005	-0.008		.011
	(0.006)	(0.004)	(0.003)	(0.006)		[.880]
Alternative (Q2)	-0.012	0.002	-0.001		-0.007	
	(0.009)	(0.005)	(0.004)		(0.007)	

Note: The table contains validity check on the regression discontinuity design in Quota 1 and 2. The density check is performed using the -rddensity- package in Stata. Balance checks are performed using -rdplot- and -rdrobust-. Income is parental income rank. Distance in GPA can only be computed within one decimal and applicants with zero distance are excluded from the density check as they are subject to a lottery.

6 GPA-based vs. holistic admissions

6.1 Validity checks

Before turning to our main results, we first perform standard checks to confirm the validity of the underlying regression-discontinuity design. The first validity test is a balancing check, where we investigate whether the applicants around the application cutoff are comparable in terms of observed characteristics that are potential confounders. Balance would be the consequence of local quasi-randomization or continuity and is required by the RD, which relies on the continuity of potential outcomes around the application cutoffs.

We implement the balancing test by estimating cutoff crossing "effects" on the background characteristics of the applicants, which are reported in columns (1)-(5) of Table 3. In the main admission quota, we consider sex, immigrant status, parental income rank, and whether applicants apply to the second admission quota. For applicants in the second admission quota, we also look at GPA. We do not find evidence of imbalance and conclude that applicants are similar on both sides of the cutoff.

As a second check, we investigate whether applicants can sort themselves around the admission cutoff. If so, this would imply that the density of GPA is not continuous around the cutoff. The last column of Table 3 shows that the estimate of the jump in the density is small and highly insignificant, and there are therefore no signs of sorting in the primary admission quota (Quota 1).[14]

[14]Since (percentile) rankings are always uniformly distributed, a bunching test for Quota 2 is not informative of selection on the margin of application.

6.2 Marginal admission rates

We begin our main analysis by documenting admission rates around the cutoff and how we estimate our estimands of interest in the fuzzy regression discontinuity design.

There are two sets of potential marginal applicants: those who only apply through Quota 1 and those who also file a Quota 2 application. Figure 4 summarizes the three first stages for these two sets of applicants. The top panel shows the first stage for applicants without a Quota 2 application when assessed on GPA in Quota 1. For these applicants, the only pathway to admission is through Quota 1, and the admission rate is therefore zero below the cutoff in Quota 1. We observe a large discontinuous jump in the admission probability at the cutoff, and above the cutoff, admission rates are about 50 percent, which reflects that applicants are often admitted to a higher prioritized program.

Applicants with a Quota 2 application have two pathways to admission and can therefore be on the margin of the two different admission quotas depending on their rankings. The two first stages are illustrated in the second-highest panel and the right panel in Figure 4. We again observe large discontinuous jumps in admission probabilities at the cutoffs, but admission rates are rising below the cutoffs. This is because of a positive correlation in the rankings in Quota 1 and Quota 2 as seen in the joint distribution of the quota-specific running variables in the large center panel of Figure 4. The marginal Quota 2 applications in the GPA-based admissions have a marginal GPA but do not clear the cutoff in Quota 2, and are therefore located at the right side of the bottom-left quadrant. Inversely, the marginal Quota 2 applicants in the holistic admissions in Quota 2 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 another cutoff, i.e. on the border of the top-right quadrant.

The first stages shown in Figure 4 relate directly to the populations of interest, the marginal applicants in each quota. In our main analysis, the complier group for the Quota 1 instrument is a mix of applicants with and without a Quota 2 application, i.e. the complier-weighted combination of the top two panels in Figure 4. The marginal applicants in Quota 2 are captured in the right panel. Our instrumental variables approach using the quota-specific instrument estimates an average effect for compliers. Thus, while the joint figure provides intuition for the design, the building blocks of our analysis are the quota-specific one-dimensional fuzzy discontinuity designs.[15]

[15] An additional advantage of the fuzzy design is that we need not worry about lack of take-up due to applicants getting better offers. In our context these applicants are never-takers.

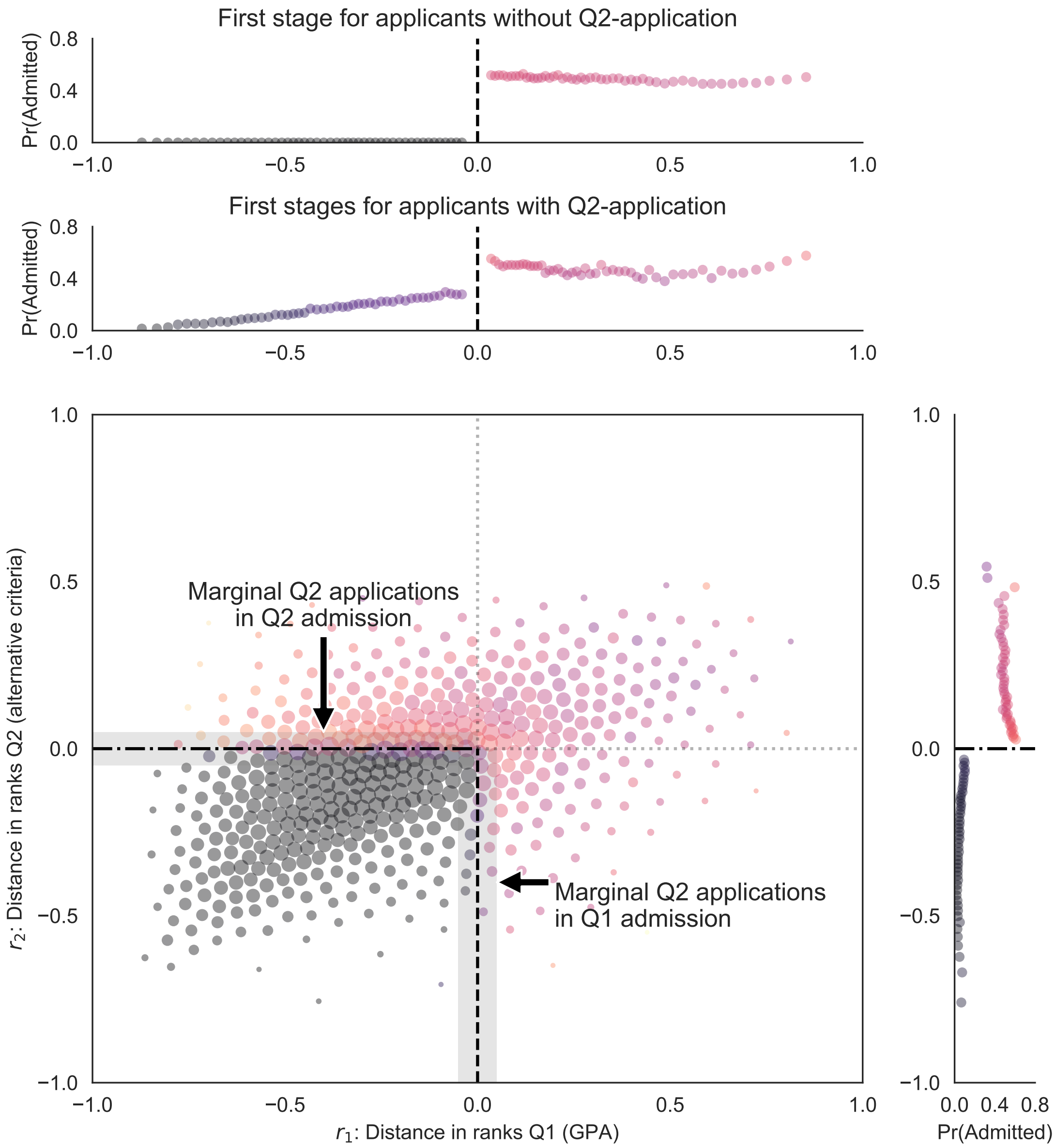


Figure 4: First stages for applicants in GPA-based (Quota 1) and holistic (Quota 2) quotas

Note: This figure illustrates the first stages in our data for applicants with and without a Quota 2 application. To preserve anonymity the center plot is constructed using K-means with 500 bins. The bins are colored according to the share admitted to the program. The top figure shows the first stage for Quota 1 applicants without a Quota 2 application. The middle and right figures show the first stages for Quota 1 and Quota 2 respectively for applicants with a Quota 2 application. Observations in the two top and right plots are clustered into 100 bins using K-means excluding 2 percentile points closest to the cutoff on either side. In our empirical analysis we do not employ K-means and keep observations close to the cutoff. Appendix Figure B2 presents the non-parametric first stages. Note that we do not control for program-year fixed effects in this figure. 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 Evaluation vs. GPA-based admission

	Program, Y^1	College, Y^1	College, $Y^1 - Y^0$
	(1)	(2)	(3)
Alternative (Q2)	0.508	0.813	0.08
	(0.011)	(0.006)	(0.012)
GPA-based (Q1)	0.477	0.796	0.016
	(0.014)	(0.005)	(0.007)
Q2 vs. Q1	0.031	0.016	0.064
	(0.012)	(0.008)	(0.014)

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 program and year. Models are estimated for program and college completion using 2SLS. Results for program value added and on-time-completion are reported in Appendix Table B2.

We return to the difference across sets of applicants with and without a Quota 2 application in Section 8.[16]

6.3 Completion rates for marginal applicants

Table 4 presents the estimated potential completion rates for marginal applicants at the GPA-based and the holistic admission margin based on the 2SLS specification outlined in equation (5). We focus on three parameters. We first report the average potential program completion rate for marginal applicants in column (1). As argued above, if programs maximize total completion, then they should equalize completion rates across the admission margins. Programs are incentivized to admit students who do well in the program, but not necessarily elsewhere. To investigate whether holistic admissions are particularly good at singling out good program matches the second column reports estimates for college completion. Finally, column (3) reports value added estimates for college completion. Differences in value added between the two admission margins are informative of how a marginal change in the relative size of the two quotas would change college completion rates of the marginal admissions.[17]

Column (1) of Table 4 shows that the completion rate of the marginal applicant who

[16]We show the quota-specific first stages in Appendix Figure B2 and report equivalent reduced forms of educational outcomes in Appendix Figure B3. The discontinuities in Figure B2 are estimated non-parametrically without fixed effects. They therefore do not correspond directly to our 2SLS estimates, though we show that the fit is similar in Appendix Figure B3.

[17]We report additional estimates of levels and value added in Appendix Table B2 where we also report results for on-time-completion.

is admitted based on holistic criteria (Quota 2) is 51 percent. This is about 3 percentage points higher than the estimated program completion rate of the marginal admission that relies only on GPA (Quota 1). While we can reject that this gap is zero, the completion rates at the two different admission margins are very close. Admission decisions of programs are therefore, on average, broadly consistent with the behavioral framework outlined in section 3.

While maximizing completion implies equalizing program completion rates across admission margins, there is no guarantee that college completion rates are then also equalized. The reason is that while programs are incentivized to minimize dropout, they have no incentive to admit applicants who, given their propensity to complete, are more likely to succeed elsewhere if they drop out of the program. If holistic admissions help programs to single out good program matches, then this could lead to lower overall college completion rates compared to the regular GPA-based admissions.

Column (2) reports the marginal college completion rates to investigate whether college completion rates are also equalized across admission margins. We see that marginal applicants are very likely to complete some form of higher education conditional on being admitted in either quota. For both admission modes, the marginal completion rate is around 80 percent. The college completion gap across the two admission margins differs by only 1.6 percentage points, and while the lower gap is consistent with the program match hypothesis, we cannot reject that the gaps are the same for program and college completion.

In the final column of Table 4 we report the value added estimates for college completion. The first row shows that for holistic admissions, the likelihood that a marginal admitted applicant completes a college degree is 8 percentage points higher when admitted to the program in question. In contrast, the value added of program admission for marginal applicants at the GPA-based admission margin is much lower at 1.6 percentage points. This difference in value added of 6.4 percent is explained by what happens when the marginal applicant is rejected, since college completion rates are similar conditional on being admitted as seen in column (2). The higher value added in Quota 2 thus reflects that the marginal applicant there is much less likely to complete higher education if rejected in a given program, than the marginal applicant in the GPA-based admissions.

To summarize, we find that completion rates of marginal applicants are very similar in the holistic and GPA-based admissions, which suggests that the model above is a good first-order description of programs' admission behavior. The value added estimates suggest that holistic admissions attract applicants with strong program-specific preferences and match effects. Moreover, the higher value added at the holistic margin suggests that overall college completion rates could be improved by increasing the relative size of holistic evaluations in college admissions and that individual programs are not (fully) internalizing the outcomes of rejected applicants.

Robustness checks In the appendix we perform extensive robustness and specification tests. In Appendix Figure B3 we verify visually that our 2SLS specification with a second-order polynomial and waiting list fixed effects is sufficiently flexible. In Table B1 we present estimates from non-parametric fuzzy-RD that line up with our estimates. We therefore conclude that the 2SLS specification with a quadratic spline and waiting list fixed effects does a good job capturing the non-linearities in the data. We also present model comparisons of estimates of average potential outcomes for program and college completion, as well as completion on time, in Appendix Table B2.

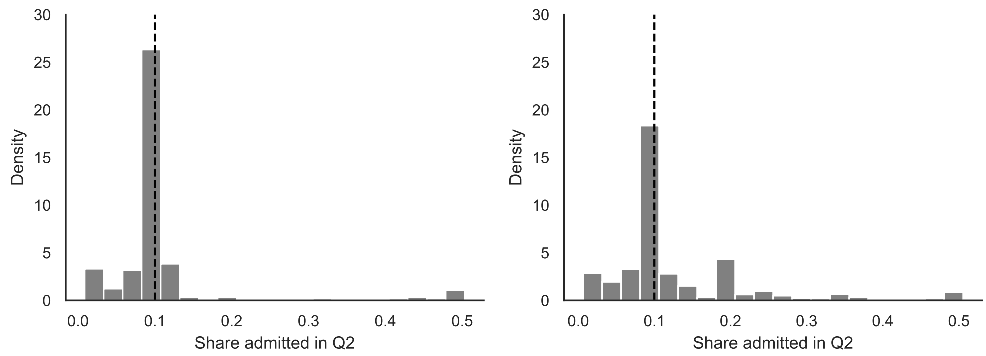
We investigate the robustness of our estimates with respect to specifications of bandwidth and flexibility of the running variable in Appendix Figure B4. To investigate whether non-compliance with admission is important, we replace admission with enrollment and reproduce Table 4 in Table B3. This modification matters little, and the qualitative takeaways are maintained.

Our central estimates are estimated by pooling across programs and years, and our estimates of quota-specific completion rates therefore represent a within-quota complier-weighted average. If the complier shares vary across quotas within programs, this pooling may be inappropriate. In Appendix Table B4 we investigate the importance of the weighting in the pooled design by estimating program-specific gaps and pooling these averages. This approach does not alter our conclusions.[18]

6.4 Exploiting changes in quota size constraints

The results above confirmed the prediction that programs equalize completion rates at the margin. These findings are from a regime where programs could set their quota sizes at will and were therefore unconstrained in their admission policy. However, before 2012, university programs could not admit more than 10 percent using holistic evaluations. The framework in Section 3 predicts that we should observe a gap in completion rates when programs are constrained from setting their quotas optimally, and that lifting the constraint should lead to a closing of such gaps. We can test this prediction by exploiting the change in regulations that relaxed the relative size of admission using holistic evaluations.

[18] Appendix Figure B5 report the full distribution of program-level estimates.



(a) 2010-2011 (b) 2012-2015

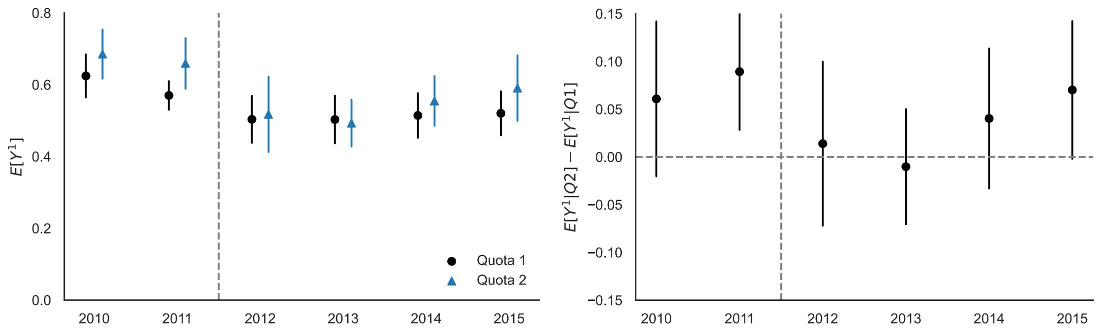
Figure 5: Share of applicants admitted in Quota 2, academic programs

Share of admitted applicants admitted using holistic 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.

Figure 5a documents that the constraint was indeed binding for a substantial group of programs. It is clearly visible that academic programs before 2012 clustered around a 10 percent share of admissions through Quota 2 in accordance with regulations. Figure 5b shows that after the constraint was lifted in 2012, the share of programs bunching around 10 percent fell, and the share with quota shares above 10 percent rose. Appendix Figures B6a and B6b show no similar increase for non-academic programs where the 10 percent limit was never binding, supporting that the change in the shares is indeed due to the lifting of the restriction on Quota 2.[19]

To exploit this change, we now include the pre-reform years 2010 and 2011 in the analysis and estimate, for each year, the gap between holistic admission (Quota 2) and admission through GPA (Quota 1). The estimates are shown in Figure 6, where we cluster standard errors at the program level and limit our data to programs present before and after the ceiling in Quota 2 was lifted. Figure 6a starts by showing the levels of the completion rates for the marginal applicants in both quotas. These tend to decrease somewhat until 2012, after which they stabilize. Figure 6b reports the corresponding completion gaps across the quotas and their 95 percent confidence intervals. Before 2012, when there was a cap on the relative size of holistic admissions, there was a positive gap across the two types of admissions, which dropped after 2012, coinciding

[19]Some of the mass to the right of the 10 percent line pre-reform is due to very small programs who cannot fulfill the requirement due to the integer nature of admission. There is some clustering around ten percent for non-academic programs before 2012. We conjecture that this is explained by programs using rules-of-thumb when choosing quota sizes.



(a) Academic programs, levels

(b) Academic programs, difference

Figure 6: Completion rate of marginal applicants in academic programs

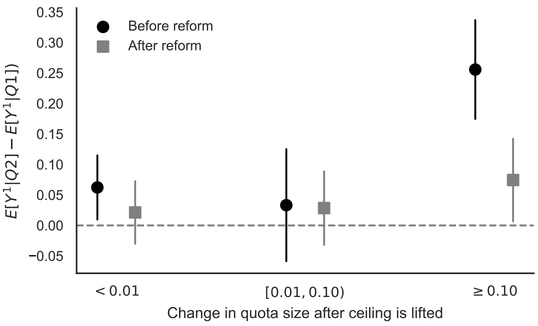
The figure shows estimates of marginal completion rates for each year with 95 percent confidence intervals. The dashed line indicates that the ceiling on quota share was lifted in 2012. The right panel shows the difference between marginal completion rates in Quota 2 and Quota 1. Standard errors are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

with the lifting of the restriction on the size of the holistic quota. We do not find a corresponding drop for non-academic programs that were not exposed to the reform, as shown in appendix Figure B7. This provides the first evidence that the lifting of the reform allowed previously constrained programs to optimize on the margin.

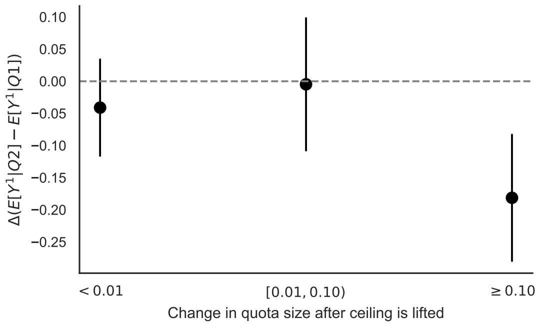
A second piece of evidence comes from examining responses to the reform by programs that were differentially constrained. As shown in Figure 5, not all programs increased the share of holistic admissions beyond ten percent once allowed. This indicates that the constraint on the quota size was not binding to the same extent for all programs. To zoom in on this margin, we divide programs into three groups: i) programs that do not increase the relative size of Quota 2, ii) programs that increase the relative size by less than 10 percentage points, and iii) programs that increase the relative size by 10 percentage points or more.[20] We then estimate across-quota admission gaps before and after the reform for these different groups and report the results in Figure 7.

Figure 7a reveals substantial differences in the completion gap across programs before the reform. While gaps are generally positive, programs that chose to increase their intake via holistic admissions by more than 10 percentage points had a gap of more than 25 percentage points before the reform. Once the reform is implemented, the gap remains essentially unchanged for all groups except for the highly constrained programs. For this group, the completion gap drops by almost 20 percentage points,

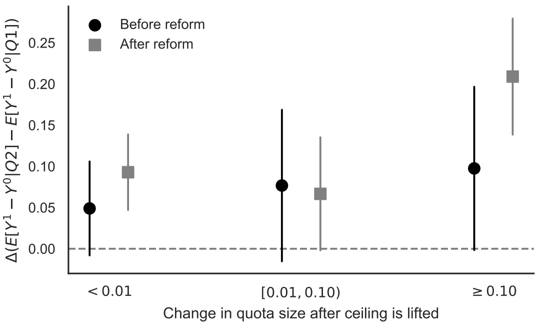
[20] In appendix Table B5 we break down the change in Quota 2 size be field and selectivity of programs. We find that the programs who increased there Quota 2 admissions by more than ten percent were predominantly selective programs, and programs within humanities and social sciences.



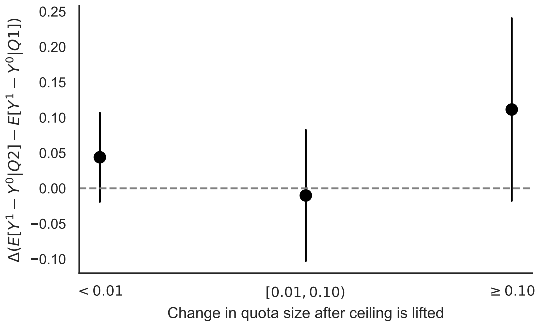
(a) Program completion gap



(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: This figure presents marginal completion rates for where we interact all endogenous variables and instruments with a categorical variable indicating the size of the change in quota 2 admissions relative to quota 1 for each program. The model is estimated on academic programs only. The dependent variable in Figure 7a and 7b is program completion multiplied by the admission indicator, which recovers Y^1. In Figure 7c and 7d the dependent variable is college completion which recovers a LATE on the extensive margin of completing college. Standard errors are clustered on the program level and the lines display 95 percent confidence intervals. We present additional results for the gaps across quotas as well as levels of potential outcomes as in terms of program and college completion in appendix Figure B8 and B9.

as seen in Figure 7b.This large pre-reform gap and subsequent fall are in line with the model's prediction for programs being constrained and re-optimizing once the constraint is lifted.

Figure 7c and 7d repeat the analysis for college value added. While these estimates are more imprecise than those of the program completion gap, the point estimate for the highly constrained programs is substantial and positive, which may suggest that Quota 2 should be expanded even more for these programs. In appendix Figure B9 we report the gap in Y^1 and Y^0 across quotas before and after the reform. We find that, similar to program completion, college completion rates if admitted, Y^1, are higher for marginal Quota 2 applicants in highly constrained programs, and that the gap dropped after the restriction was lifted. The difference is, however, estimated very imprecisely. In contrast, the estimates for college completion rates for the marginally not-admitted,

Y^0, exhibit a sharp and precisely estimated drop after the reform. As programs increase their intake via Quota 2 they are admitting applicants who do relatively well in the program, but who have progressively worse outside options.

To summarize, the reform analysis reinforces the finding above that the theoretical setup in Section 3 is a good description of programs' admission behavior. The value added estimates from the reform also suggest that holistic admissions attract applicants with strong program-specific preferences and match effects, and that overall college completion rates could be improved further by increasing the importance of holistic admissions in college admissions.

6.5 Additional objectives in college admissions?

As discussed in section 3 programs may have other objectives than profit-maximization which may result in gaps in marginal completion rates. Moving a slot from GPA-based admission to holistic admission involves exchanging one applicant for another. We do not expect these applicants to have the same characteristics, and if programs care about these characteristics a completion gap can be informative of program preferences for certain types of applicants.

To investigate whether the completion gaps reflect other objectives we characterize the composition of the marginal applicant at the two margins in our reference period. Though the marginal applicants are not directly identified in data we can estimate distributional characteristics by following Abadie (2003) and exchanging the dependent variable Y_{ipqt} in equation (5) for covariates. The parameter on the treatment variable is then an estimate of the average value of a characteristic among the marginal applicants. We present the results in Table 5.

Marginal applicants in GPA-based admission have mechanically a higher GPA. In terms of their demographic background characteristics we see that they are relatively more likely to be female, younger, and from an immigrant background. We do not observe differences in parental income. This suggests that a relative increase in the use of holistic admissions will likely favor males, native Danes and older applicants.

The characterization of the marginal admissions also aids in the interpretation of the across-quota completion gap. As pointed out in Section 3, a positive gap can arise when Quota 2-applications are elastic and when programs are trading off infra-marginal composition and information benefits of holistic screening and screening cost. However, gaps can also arise when programs value other characteristics than potential completion. If this is the case, then programs should be willing to accept lower expected marginal completion in a quota in order to admit certain applicants. The last column in

Table 5: Characteristics of marginal applicants

	GPA-based (Quota 1)		Holistic (Quota 2)	
	est.	se.	est.	se.
High school GPA rank	0.59	0.01	0.43	0.01
Female	0.63	0.01	0.61	0.01
Age	21.22	0.03	22.57	0.07
Immigrant	0.11	0.00	0.09	0.01
Parental income rank	0.74	0.00	0.74	0.00
Predicted completion given characteristics	0.50	-	0.46	-

Note: The table shows the estimated characteristics of marginal applicants in GPA-based admission (Quota 1) and holistic admission (Quota 2) respectively. The characteristics are estimated by exchanging the dependent variable Y_{ipqt} in equation (5) with covariates. Standard errors are clustered on program-year level. We do not observe parental income for 1.2 percent of the sample and exclude these observations from the estimates in the fourth line. To predict completion based on the characteristics we estimate a logit model interacted with field dummies and include field fixed effect on the subset of admitted applicants. We then form a prediction for all applicants in the samples based on this model. We do not report standard errors for the predicted completion of compliers, as they do not take into account the uncertainty in forming the prediction.

Table 5 shows that the characteristics of the marginal Quota 1 applicant predict a higher completion rate than the characteristics of the marginal Quota 2 applicant. If programs would value other characteristics than the likelihood of completion, we would expect the marginal Quota 2 applicant to underperform relative to the marginal Quota 1 applicant. This is not the case, as shown in Table 4. We therefore interpret this evidence as supportive of the profit-maximizing model of programs' capacity setting over non-academic considerations in program admissions.[21]

7 Program level heterogeneity

We now investigate cross-program heterogeneity in light of the role of screening costs in our theoretical model: if the marginal Quota 2 admission outperforms the marginal Quota 1 admission, this is consistent with endogenous sorting and screening costs. Further, heterogeneity in gaps in college completion value added informs us about which program incentives may be misaligned with social objectives. To investigate heterogeneity across programs, we return to our baseline sample and the reference period when programs could choose the share admitted through each quota freely.

We examine heterogeneity along three dimensions: i) holistic admissions as a share

[21] In Gandil and Leuven (mimeo) we investigate bias in ranking within Quota 2 towards or against minorities.

of total admissions, ii) selectivity of the program, and iii) evaluation criteria in holistic admission. We stress that these characteristics are determined (at least partly) by the optimizing program and thus are not exogenous.[22]

First, we examine how program outcomes vary with their reliance on holistic admissions (Quota 2). If programs make extensive use of holistic evaluations, then this suggests that they perceive substantial benefits from improved screening and sorting. However, at the margin, screening costs may eventually prevent programs from expanding the size of their holistic admissions and from equalizing completion rates across the admission margins. Figure 8a shows marginal completion rate differences by programs' reliance on holistic screening. Most programs show no significant gap in marginal completion rates between quotas. However, programs with high Quota 2 intake exhibit a 6 percentage point gap, suggesting that screening cost considerations become binding as holistic admissions expand.

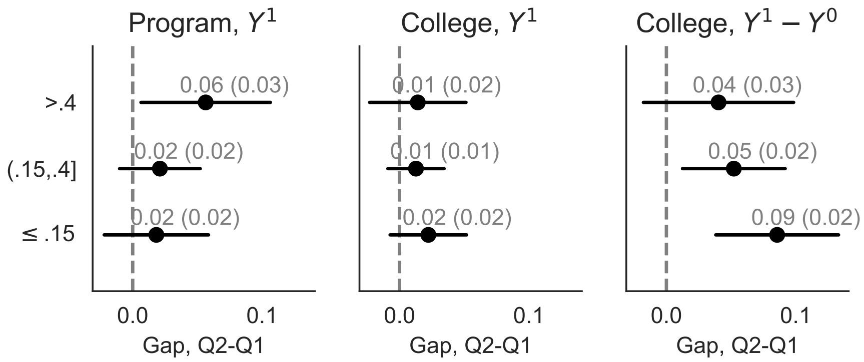
Although overall college completion rates are similar between quotas, the value added at the margin varies systematically with Quota 2 usage (Figure 8a, right panel). Programs with low Quota 2 shares show a 9-percentage-point advantage in value added, but this gap diminishes to a statistically insignificant 4 percentage points in programs heavily using holistic evaluation. In other words, the results suggest that the programs that would generate the most benefits for society by expanding holistic admissions are the ones currently using this channel the least.[23]

Second, we consider program selectivity as measured by the GPA cutoff in Quota 1 in the previous year. For a given applicant, higher selectivity in Quota 1 makes filing a Quota 2 application more beneficial in expectation. If programs incur non-trivial screening costs, it can be beneficial to discourage Quota 2 applications by limiting admission prospects through Quota 2. The leftmost figure of Figure 8b reports estimates of the program completion rate gap by selectivity. We find small and insignificant gaps for all groups of selectivity, though point estimates suggest somewhat larger gaps of around 5 percentage points for highly selective programs compared to 1-2 percentage points for less selective ones. This is consistent with programs lowering access through Quota 2 to limit screening costs.

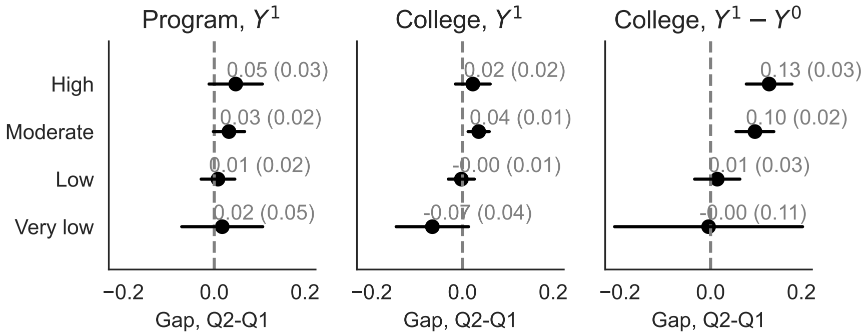
We do not find any gaps in college completion rates. However, in terms of value added, we observe notable differences across selectivity levels. The marginal holistic

[22] We report heterogeneity in gaps by field in appendix Figure B11.

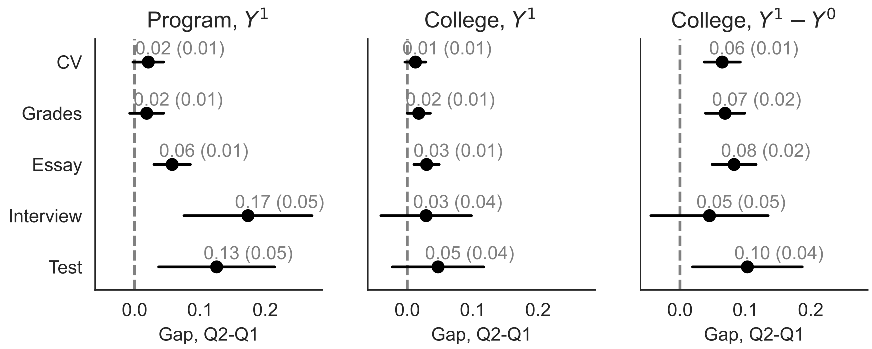
[23] While we cannot reject the null that there is no difference across program for these broad categories (see Table B6), 2SLS estimates (not reported here) that exploit all variation in Q2 shares gives a coefficient (s.e.) of 0.08 (0.013) on the interaction of the Q2 share and the gap for Y^1, and -0.014 (0.008) for college $Y^1 - Y^0$.



(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 - GPA, by program characteristics

Note: The figures report results for different subsets of programs. The leftmost figure shows differences between marginal program completion rates between holistic admission (Quota 2) and GPA-based admission (Quota 1). The middle figures show the same for overall college completion rates. The rightmost 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. In Figure 8a importance of holistic admissions is measured by the share of admitted applicants, who are admitted through Quota 2. Selectivity of programs in Figure 8b is coded as follows: Very low (Cutoff below 4), Low (Cutoff below 7), Moderate (Cutoff below 10), High (Cutoff above or equal to 10). Cutoffs are from the year before the observation. In Figure 8c programs are included if they use a given criterion. Programs use multiple criteria, and the sets of programs behind each estimate overlap. Appendix Figure B10 presents results for all combinations of criteria. Appendix Figures B6,B7 and B7 present formal test of differences across categories of programs.

admit in highly selective programs shows substantially higher value added in terms of college completion compared to the marginal GPA-based admit, with gaps of around 13 percentage points. This large difference in value added, despite similar completion rates conditional on admission, suggests that marginal holistic applicants to selective programs have markedly worse outside options than their GPA-quota counterparts.[24] This pattern aligns with strong program-specific preferences or match effects among holistic applicants to selective programs—these appear to be students who would excel in their chosen program but struggle to complete college if rejected.

Third, we investigate how patterns differ based on specific holistic evaluation criteria. We expect screening costs to vary across criteria. For example, we do not expect interviews as a screening technology to exhibit economies of scale, and programs, therefore, have a clear incentive to deter low-quality applicants if they use interviews for screening. In contrast, reviewing grades in specific subjects may be cheaper to scale. We repeat the analysis where we condition on using each of the kind of criteria available and present the results in Figure 8c. Gaps in marginal completion rates are high in programs using interviews (17 percentage points) and tests (13 percentage points). These large gaps are consistent with large screening costs. While tests might scale better than interviews, the positive gap suggests that this is not so. However, tests are most often used in combination with interviews, making the individual contribution of each criterion difficult to disentangle.[25] The smaller but positive gap for programs using essays (6 percentage points) and the absence of gaps for programs using CVs or grades suggest that these criteria impose lower marginal screening costs than interviews and tests.

We do not observe heterogeneity in marginal college completion rates or value added in terms of college completion by choice of criteria. All types of criteria are associated with positive value added gaps ranging from 6 to 10 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.

[24] We can reject the null that there is no difference across groups of low selectivity programs versus moderately or highly selective programs, see Table B7 for the formal tests.

[25] The combinations of criteria are shown in Appendix Figure B1. For the subset of programs using only test, we cannot reject that the program completion gap is zero, though the estimate is imprecise as seen in Appendix Figure B10. We cannot generally reject the null that there is no difference across program usage of assessment criteria. Table B8 shows the formal tests.

8 Sorting and screening

As highlighted in Section 3, the benefits of holistic admissions potentially come from two distinct channels: sorting and screening. To illustrate this, consider admitting the first marginal holistic applicant. The first thing this does is substitute someone who applied to the holistic admissions for an applicant from the regular application pool. This tends to be beneficial to the program if there is positive sorting into holistic admissions. The second potential benefit of holistic admissions is the possibility of screening applicants on alternative criteria as opposed to GPA.

Differences between admission regimes that use alternative criteria can therefore arise because of selection into application and because other evaluative criteria may admit different applicants conditional on selection. The relative importance of these channels can inform the design of college admissions. If sorting dominates, then imposing costs on applicants is more important than using the additional information provided. In contrast, if screening dominates, then the criteria provide useful information on the potential completion rate of applicants.

Screening and sorting can be made precise by considering 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 are readily estimated at the GPA admission margin.

The first term, $E(y^1 \mid r_1 = a, r_2 \geq b, Q2 = 1)$, is the average y^1 for Quota 2 applicants who are ranked above the application cutoff in Quota 2 (i.e. $r_2 \geq b$) and who are admitted through holistic admissions. In the current setup, these are Quota 2 applicants who are always-takers at the GPA cutoff a. We can estimate y^1 for always-takers by estimating equation (5) with 2SLS, but with the dependent variable now equaling $Y_{ipt}(1 - z_{1ipt})A_{ipt}$ and with $(1 - z_{1ipt})A_{ipt}$ as the endogenous variable.

The second term, $E(y^1 \mid r_1 = a, Q2 = 0)$, is the average potential outcome on admission for the marginally admitted applicant who did not apply to the holistic admissions, and these are therefore regular compliers in the GPA admissions pool without a Quota 2 application.[26]

The performance gap between the two applicant groups at the GPA admission mar-

[26] There are no always-takers for this group as illustrated by the zero admission rate to the right-hand side of the cutoff in the first-stage graph in the top panel in Figure 4

gin can be decomposed into the following two components:

$$E(y^1 \mid r_1 = a, r_2 \geq b, Q2 = 1) - E(y^1 \mid r_1 = a, Q2 = 0) = \underbrace{E(y^1 \mid r_1 = a, r_2 \geq b, Q2 = 1) - E(y^1 \mid r_1 = a, Q2 = 1)}_{\text{Screening}} + \underbrace{E(y^1 \mid r_1 = a, Q2 = 1) - E(y^1 \mid r_1 = a, Q2 = 0)}_{\text{Sorting}}. \quad (7)$$

where the first component is the benefit that comes from screening holistic-admission applicants on alternative information rather than GPA alone. The second component quantifies the sorting into holistic admission, which can lead to differential performance between the applicants who applied there and those who chose not to apply to the holistic admissions.

To estimate the screening and sorting components, we need to recover one more term, namely $E(y^1 \mid r_1 = a, Q2 = 1)$, which in the current setup consists of both the compliers and the always-takers at the GPA admission margin for the Quota 2 applicants. This term is estimated in our 2SLS setup, with the dependent variable now set to $Y_{ipt} z_{1ipt} A_{ipt}$ and the endogenous variable to $z_{1ipt} A_{ipt}$.

Figure 9 reports the estimates of the sorting and screening components in the decomposition of the completion gap between Quota 2 and the other applicants at the GPA admission margin. We observe strong positive sorting, which shows that applicants who apply to the holistic assessments have 6.2 percentage points higher potential completion rates than regular applicants with a similar GPA. Positive sorting aligns with higher application costs in holistic assessment, which causes applicants to self-select. The screening component is smaller and negative, which suggests that for always-takers, the completion rates are decreasing in r_2 at the margin of admission in the GPA-based quota. This can either indicate a failure to adequately predict graduation from the additional information generated in the holistic admissions, or it could point to programs having other objectives than maximizing completion.

While the aggregate decomposition reveals that positive sorting is the dominant channel through which holistic admissions improve outcomes, with little or even negative returns to screening, these average effects may mask important heterogeneity. Indeed, our previous analysis of completion gaps showed substantial variation across program characteristics in both program-specific and system-wide outcomes. To better understand how the relative importance of sorting and screening varies across programs, we examine the same three dimensions: the extent of Quota 2 usage, program selectivity, and evaluation criteria. This analysis can help explain why some programs make

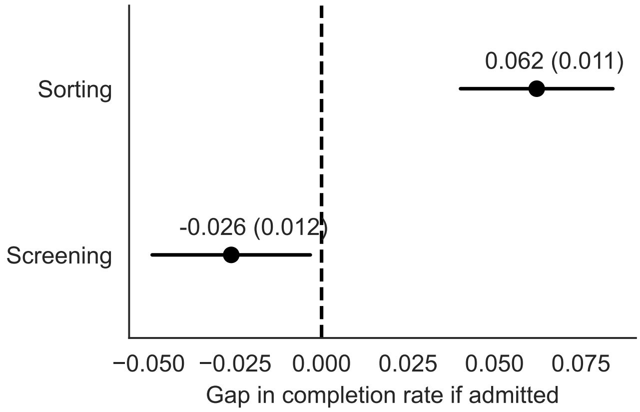


Figure 9: Sorting and screening decomposition of across-quota marginal program completion gap

Note: Decomposition estimates of the screening and sorting decomposition in equation (7). Sorting is estimated as the difference in the program completion rate of marginal admissions at the GPA margin with and without a Quota 2 application. Screening is estimated as the difference in the program completion rate of Quota 2 applicants at the GPA admission cutoff who are admitted based on the subjective assessment compared to all marginal admissions.

greater use of holistic admissions than others, and whether the limited screening benefits we observe on average reflect universal challenges in going beyond GPA or varying screening capabilities across programs.

Figure 10a reports how the sorting and screening components vary with programs' reliance on holistic admissions. Programs that make extensive use of Quota 2 show little evidence of sorting benefits but achieve positive screening benefits. When a large share of applicants is admitted through Quota 2, there is mechanically less scope for positive selection into the Quota 2 applicant pool. However, these programs appear to effectively use the additional information from holistic assessment to identify strong candidates, which could suggest that they have effective evaluation methods.

In contrast, programs that make moderate use of holistic admissions experience substantial positive sorting effects. For programs that make very limited use of Quota 2, we observe both positive sorting and also a large negative screening component. This suggests that while they attract strong applicants through Quota 2 (perhaps precisely because few are admitted this way), they may either lack the expertise or resources to effectively screen these applicants or simply observe too few of them to develop informative priors. These patterns are consistent with programs' extent of Quota 2 usage reflecting their relative advantages in screening versus sorting: programs that have developed effective screening capabilities make greater use of holistic admissions, while those that mainly benefit from sorting but struggle with screening tend to use

Quota 2 more sparingly.

Figure 10b reports the decomposition by program selectivity. These results suggest that holistic admissions generate positive sorting across the board. With the exception of the least selective programs, we find, however, no evidence of any benefits or disadvantages of the additional screening. For programs that are very little selective, the screening component is large and negative: conditional on their GPA, the marginal applicants in the regular GPA-based admission who score higher in the subjective ranking are substantially less likely to complete the program than the lower-ranked applicants, to the extent that it completely offsets the positive sorting.

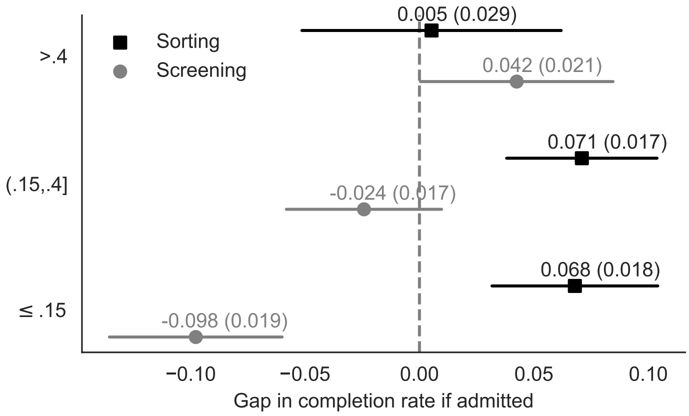
The universal presence of positive sorting effects across all selectivity levels suggests that the application costs associated with holistic admissions help attract students who are more likely to succeed. This is perhaps surprising for highly selective programs, where we might have expected less scope for positive selection given their already high-achieving applicant pool. The persistence of sorting benefits even at high selectivity levels suggests that holistic application requirements help identify motivated and well-matched students even among high-GPA applicants.

The large negative screening component for the least selective programs suggests that these programs struggle to effectively use the additional information from holistic evaluation to identify strong candidates in a pool of very low GPA students. This could reflect either limitations in their screening capabilities or that GPA is a relatively stronger predictor of success for lower-achieving students.

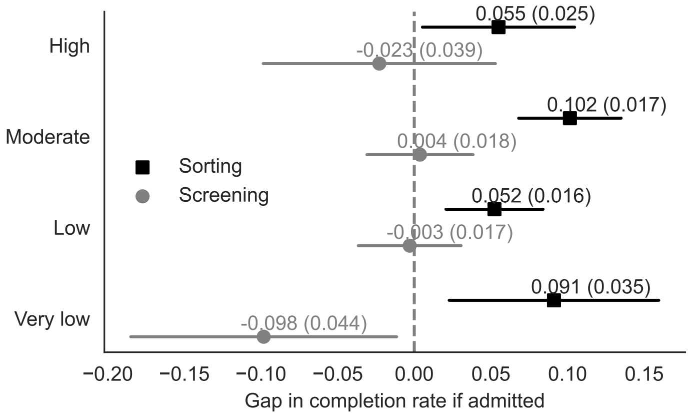
Figure 10c shows strong heterogeneity in both sorting and screening effects across different evaluation criteria. Programs using interviews or tests show particularly strong positive sorting effects, roughly double the magnitude observed for programs using CVs, grades, or essays. This pattern aligns with the higher costs these criteria impose on applicants - preparing for and attending interviews or taking additional tests requires substantial time and effort compared to submitting existing grades or writing an essay.

However, for these same programs using interviews or tests, we also observe large negative point estimates for the screening component, though these estimates are relatively imprecise. This suggests that despite (or perhaps because of) the strong positive sorting, these programs struggle to effectively use the additional information from interviews and tests to identify the best candidates among those who apply. Programs using other criteria like CVs, grades, or essays show small and statistically insignificant screening components.

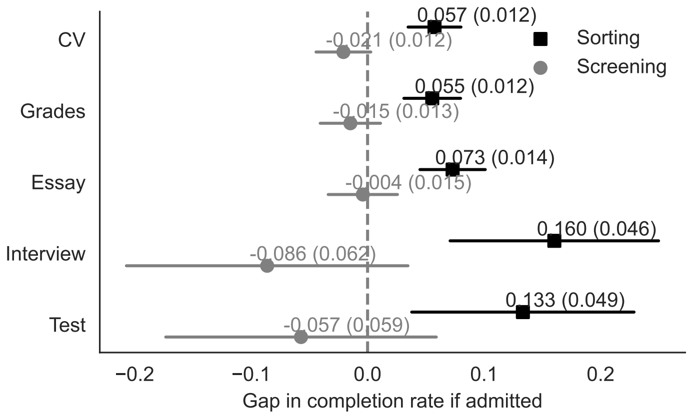
The evaluation methods that appear most effective at inducing positive sorting through high application costs also seem least effective at screening, though the imprecision of these estimates warrants caution in interpretation. Moreover, criteria themselves are



(a) By importance of holistic admissions



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



(c) By evaluation criteria

Figure 10: Sorting and screening decomposition

Note: Decomposition estimates of the screening and sorting decomposition in equation (7) for subsets of programs. The method is described in the note for Figure 9. The categories are described in the note for Figure 8.

also chosen by programs, introducing potential selection bias, and programs often use multiple criteria in combination for Quota 2 assessments. This makes it difficult to isolate the impact of any single criterion. Appendix Figure B12 reports estimates by all criteria combinations.

The decomposition analyses reveal that the benefits of holistic admissions arise primarily through advantageous self-selection - higher-potential students are more likely to apply through the holistic track. In contrast, the additional information gained through holistic screening appears to provide relatively little benefit beyond what is captured by GPA. This pattern varies systematically across programs: while positive sorting appears universal except where mechanical constraints limit its scope (programs with large Quota 2 shares), screening effectiveness differs notably. Programs extensively using holistic admissions show some screening benefits, while the least selective programs struggle to effectively use information beyond GPA. Evaluation criteria that impose higher application costs, like interviews and tests, are associated with stronger positive sorting but appear less effective at screening, though these estimates are imprecise and reflect programs' endogenous choice of evaluation methods.

Additional results and robustness checks We perform robustness checks of the decompositions with respect to choice of bandwidth and parametric specifications in the appendix. Figure B13 shows the robustness of aggregate sorting, while Appendix Figure B14, B15 and B16 show robustness of the estimates stratified by importance of Quota 2, selectivity, and criteria respectively. In Appendix Figure B17 we report decomposition results stratified by field and provide robustness checks of the field-specific estimates in appendix Figure B18.

9 Conclusion

In this paper, we provide the first comprehensive analysis of college admissions when programs can choose between different screening technologies. We make several contributions. First, we develop and test a theoretical framework that explicitly models how programs trade off the costs and benefits of different admission channels. Second, by exploiting detailed administrative data covering both admission tracks in Danish higher education, we overcome the measurement and selection challenges that have limited many previous studies of admission mechanisms. This allows us to provide unbiased estimates of counterfactual completion rates of marginal applicants across admission channels, as well as causal effects of admission across admission modalities. Third, we develop and implement a novel decomposition that separates the benefits of holistic admissions into screening and sorting effects.

Our findings show that programs effectively optimize their own completion rates through admission decisions. When unconstrained, they achieve remarkably similar completion rates across quotas. We find independent evidence that is consistent with program optimization by exploiting a reform that lifted restrictions on holistic admission quota sizes - previously constrained programs showed higher completion rates in holistic quotas that converged to GPA-quota rates once the constraints were lifted.

A key insight from our analysis is that the benefits of holistic admissions arise primarily through advantageous self-selection rather than better screening. We find that higher-potential students are more likely to apply through the holistic track, while the additional screening information provides relatively little benefit beyond GPA. This pattern holds across program characteristics, though with variation—more selective programs and those using high-cost evaluation criteria like interviews show particularly strong sorting benefits.

However, our results reveal a disconnect between program-level and system-wide optimization. While programs effectively maximize their own completion rates, rejected marginal applicants from the holistic quota are 6.4 percentage points less likely to complete higher education elsewhere compared to their GPA-quota counterparts. This suggests substantial unrealized gains in overall college completion that individual programs fail to internalize.

These findings have potential implications for education policy. While performance-based incentives successfully encourage programs to optimize their own outcomes, achieving broader societal goals of educational attainment may require incentives that account for system-wide effects. The challenge lies in designing such incentives, given the inherent difficulty of measuring outcomes beyond individual program-specific outcomes. Our results suggest that particular attention should be paid to policies that facilitate beneficial applicant sorting while managing screening costs.

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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:

$$\begin{aligned}
&\max_{a,b} E(y^1 \mid \text{offer} = 1) \Pr(\text{offer} = 1) - C(\Pr(\text{offer} = 1)) \\
&\quad = \max_{a,b} \int_0^1 \int_0^1 E[y^1|r_1, r_2] f(r_1, r_2) dr_2 dr_1 - \int_0^a \int_0^b E[y^1|r_1, r_2] f(r_1, r_2) dr_2 dr_1 \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad - C(1 - \int_0^a \int_0^b f(r_1, r_2) dr_2 dr_1),
\end{aligned}$$

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

$$\alpha \Pr(\text{offer} = 1) \geq \Pr(r_1 < a, r_2 \geq b) \tag{8}$$

gives the following FOCs

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

where λ is the Lagrange multiplier on the constraint (8). These can be rewritten as

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

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 consider whether to apply for admission in the secondary quota ($Q2$) where other criteria are used. Their utility when admitted to the program equals U_1 and their utility when not admitted is U_0.

Applicants who decide to apply to the secondary quota must provide additional information I at a cost $AC(I) > 0$. Applicants apply to the secondary quota and provide information I if in expectation expected benefits of applying which equals the (expected) probability of not being admitted through Quota 1 but crossing the threshold in Quota 2 times the gains $U_1 - U_0$ minus the application cost $AC(I)$:

$$\begin{aligned}\Pr(r_1 < a \wedge r_2 \geq b \mid I)(U_1 - U_0) - AC(I) > 0 \\ \frac{AC(I)}{\Delta U} < \Pr(r_1 < a \wedge r_2 \geq b \mid I)\end{aligned}$$

The share of applicants that apply to Quota is therefore a function of the cutoffs a and b:

$$P2 \equiv \Pr(Q2 = 1) = G(\Pr(r_1 < a \wedge r_2 \geq b))$$

with $G(\cdot)$ being the the CDF of $\frac{AC(I)}{\Delta U}$.

With endogenous Q2 applications the program's objective function now becomes

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

where $SC(\cdot)$ is screening cost which depends on the size of the pool of applicants to Quota 2, and $C(\cdot)$ is the offer cost.

When Q2 applications are inelastic it can be shown that that the admission cutoffs are set to equalize the expected completion rates for marginal applicants at these cutoffs equal to the marginal cost of admission:

$$E(y^1 \mid r_1 = a, Q2=0)\omega + E(y^1 \mid r_1 = a, r_2 < b, Q2=1)(1-\omega) \\ = E(y^1 \mid r_1 < a, r_2 = b, Q2=1) = C' \quad (9)$$

where the first term corresponds to the expected completion rate for marginal applicants for GPA based admissions ($r_1 = a$) which consist of Q2=0 applicants and Q2=1 applicants who would not qualify in Q2 ($r_2 < b$). The second term is the expected completion rate for Q2-applicants at the margin of alternative admissions ($r_2 = b$) who would not quality based on GPA ($r_1 < a$).

However, elastic Q2 applications introduce two additional considerations for the program, the first is that the size of the Quota 2 applicant pool is endogenous to the cutoffs, and the second is that the potential outcome distribution of the Quota 2 applicants also may change:

$$P2_x \equiv \frac{\partial}{\partial x}\Pr(Q2=1) \neq 0, \quad x \in (a,b)$$
$$f2_x \equiv \frac{\partial}{\partial x} f(r_1, r_2 \mid Q2=1) \neq 0, \quad x \in (a,b)$$

If we for notational convenience define admission in Q2 as $A2 \equiv \{r_1 < a, r_2 \geq b\}$, then we get the following FOCs:

$$\frac{\partial}{\partial a} = -E(y^1 \mid r_1 = a)f(a) \tag{10}$$

$$+E(y^1 \mid r_1 = a, r_2 \geq b, Q2 = 1)\Pr(r_2 \geq b \mid r_1 = a, Q2 = 1)P2 \tag{11}$$

$$+E(y^1 \mid A2 = 1, Q2 = 1)\Pr(A2 = 1 \mid Q2 = 1)P2_a \tag{12}$$

$$+\int_0^a \int_b^1 y^1(r_1, r_2) f2_a dr_2 dr_1 P2 \tag{13}$$

$$-SC'P2_a \tag{14}$$

$$-C'[-f(a) + \Pr(r_2 \geq b \mid r_1 = a, Q2 = 1)P2 \tag{15}$$

$$\Pr(A2 = 1 \mid Q2 = 1)P2_a \tag{16}$$

$$+\int_0^a \int_b^1 f2_a dr_2 dr_1 P2] = 0 \tag{17}$$

$$\frac{\partial}{\partial b} = -E(y^1 \mid r_1 < a, r_2 = b, Q2 = 1)\Pr(r_1 < a \mid r_2 = b, Q2 = 1)P2 \tag{18}$$

$$+E(y^1 \mid A2 = 1, Q2 = 1)\Pr(A2 = 1 \mid Q2 = 1)P2_b \tag{19}$$

$$+\int_0^a \int_b^1 y^1(r_1, r_2) f2_b dr_2 dr_1 P2 \tag{20}$$

$$-SC'P2_b \tag{21}$$

$$-C'[-\Pr(r_1 < a \mid r_2 = b, Q2 = 1)P2 \tag{22}$$

$$+\Pr(A2 = 1 \mid Q2 = 1)P2_b \tag{23}$$

$$+\int_0^a \int_b^1 f2_b dr_2 dr_1 P2] = 0 \tag{24}$$

Consider what happens when the program reduces the Quota 1 size by increasing its application cutoff a. As before, this lowers completion at Quota 1 margin by the sum of (10) and (11). However, what is different compared to the case where Quota 2 applications are inelastic, is that now the program also has infra-marginal considerations.

First there is an extensive margin channel through (12) which captures an increase in completion through Quota 2 admissions because the *size* of the Q2 application pool increases. Second there is an intensive margin channel through (13) which captures the change in completion of Quota 2 admissions due to changes in the *composition* of the Q2 applicant pool. This term is probably negative as an increase in the Quota 1 application cutoff is expected to decrease the quality of the Quota 2 applicant pool as now more people apply there. Finally, screening cost increase as $P2_a > 0$ and more people apply to Quota 2 which is reflected by the term (14).

Reducing the size of Quota 1 also lowers admission costs by the mass of the marginal applicants in Quota 1 in (15), while there is a partial increase in admission costs because more applicants are admitted through Quota 2 as more people apply there (16), and because of the changes in the composition of the Quota 2 applicant pool (17).

A change in the Quota 2 size results in comparable mechanisms. First there is the change in completion coming from the marginal applicants (18), then there are infra-marginal impacts through the extensive (19) and intensive changes (20) in the Quota 2 applicant pool. Note that a marginal increase in b reduces the screening cost (21) since $P2_b < 0$.

Taken together these infra-marginal responses and screening costs introduce a wedge between the completion rates of the marginal applicants in Quota 1 and 2 in (9). Screening cost unambiguously generate a positive wedge, but the other components can can vary in their sign and size. This is shown in Section A.2, where we develop a numerical simulation model to quantitatively investigate these comparative statics.

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:

$$(1 - Pr(\sigma_1 > a|y))Pr(\sigma_2 > b|y) > s, \tag{25}$$

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:

$$max_{a,b} E[y|A]Pr(A) - \frac{c}{2}Pr(A)^2 - \frac{d}{2}Pr(Q2)^2, \tag{26}$$

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.

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

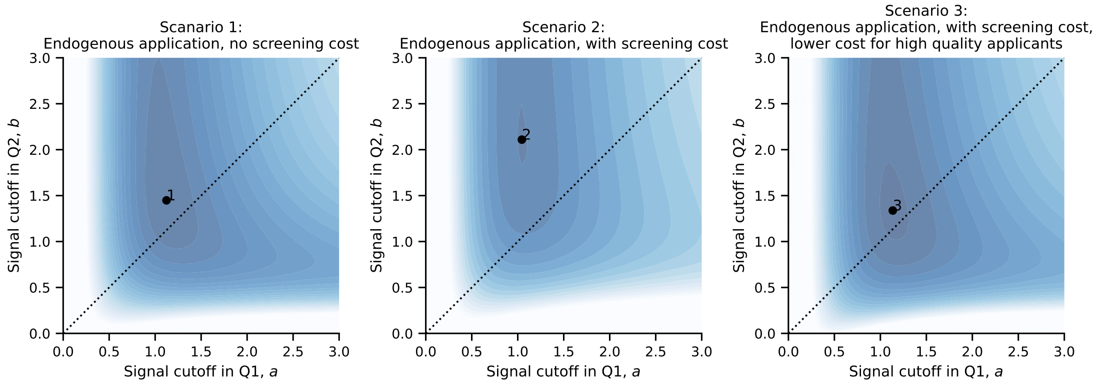


Figure A1: Objective function in cutoff space

Note: The figures show the countures of the objective function in Equation (26) 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.

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

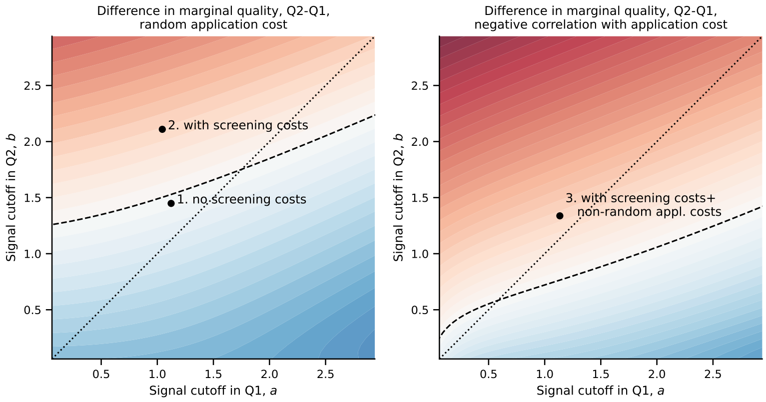


Figure A2: Marginal quality gap in cutoff space

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.

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.

B Additional figures and tables

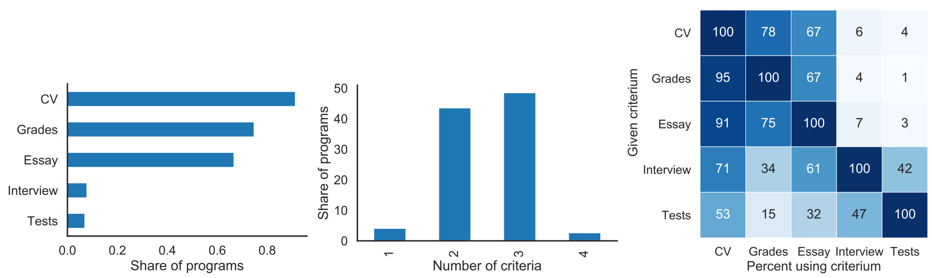


Figure B1: Combination of criteria

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

Table B1: Potential program and college completion rates and value added - GPA-based admission vs. Alternative Evaluation

	Program, Y^1		College, Y^1		College, $Y^1 - Y^0$	
	(1)	(2)	(3)	(4)	(5)	(6)
Alternative (Q2)	0.498	0.508	0.81	0.813	0.054	0.08
	(0.015)	(0.012)	(0.009)	(0.006)	(0.016)	(0.01)
GPA-based (Q1)	0.486	0.477	0.808	0.796	0.028	0.016
	(0.017)	(0.011)	(0.012)	(0.004)	(0.019)	(0.006)
Q2 vs. Q1	0.012	0.031	0.002	0.016	0.026	0.064
	(0.017)	(0.011)	(0.016)	(0.008)	(0.024)	(0.014)
Estimator	RD	2SLS	RD	2SLS	RD	2SLS

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 bootstrapped with 200 replications clustered by program and year. Models are estimated for program and college completion using 2SLS and fuzzy RD estimated in Stata using the rdrobust-package. Results for program value added and on-time-completion are reported in Appendix Table B2.

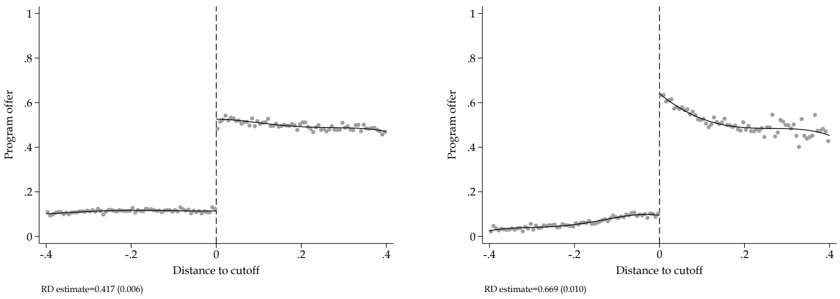
Table B2: Potential completion in time and value added – GPA-based admission vs. Alternative Evaluation

	Program, Y^1		Program, Y^0		Program, $Y^1 - Y^0$	
	RD	2SLS	RD	2SLS	RD	2SLS
Alternative (Q2)	0.498	0.508	0.216	0.197	0.282	0.311
	(0.017)	(0.015)	(0.012)	(0.008)	(0.02)	(0.015)
GPA-based (Q1)	0.486	0.477	0.285	0.212	0.198	0.266
	(0.015)	(0.01)	(0.014)	(0.006)	(0.017)	(0.008)
Q2 vs. Q1	0.012	0.031	-0.069	-0.015	0.084	0.045
	(0.017)	(0.011)	(0.018)	(0.009)	(0.026)	(0.015)

	College, Y^1		College, Y^0		College, $Y^1 - Y^0$	
Estimator	RD	2SLS	RD	2SLS	RD	2SLS
Alternative (Q2)	0.81	0.813	0.756	0.733	0.054	0.08
	(0.011)	(0.007)	(0.014)	(0.011)	(0.018)	(0.012)
GPA-based (Q1)	0.808	0.796	0.776	0.781	0.028	0.016
	(0.013)	(0.005)	(0.014)	(0.006)	(0.018)	(0.008)
Q2 vs. Q1	0.002	0.016	-0.02	-0.048	0.026	0.064
	(0.016)	(0.008)	(0.021)	(0.012)	(0.024)	(0.014)

	Completes in time, Y^1		Completes in time, Y^0		Completes in time, $Y^1 - Y^0$	
	RD	2SLS	RD	2SLS	RD	2SLS
Alternative (Q2)	0.474	0.483	0.186	0.166	0.289	0.316
	(0.016)	(0.013)	(0.011)	(0.007)	(0.018)	(0.013)
GPA-based (Q1)	0.466	0.452	0.238	0.179	0.224	0.273
	(0.015)	(0.009)	(0.013)	(0.006)	(0.018)	(0.009)
Q2 vs. Q1	0.008	0.031	-0.052	-0.012	0.065	0.043
	(0.018)	(0.011)	(0.016)	(0.007)	(0.023)	(0.013)

The table contains estimated potential completion rates (Y^1) and value added ($Y^1 - Y^0$ with standard errors in parentheses. Standard errors are bootstrapped with 200 replications. Models are estimated for program and college completion using 2SLS and fuzzy RD estimated in Stata using the rdrobust-package.



(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.

Table B3: Potential program and college completion rates and value added - GPA-based admission vs. Alternative Evaluation - Enrollment as endogenous variable

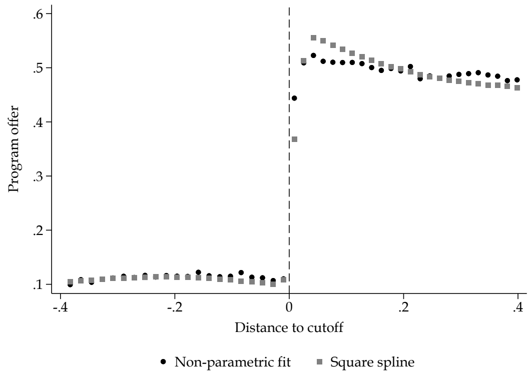
	Program, Y^1	College, Y^1	College, $Y^1 - Y^0$
Q2	0.579	0.85	0.124
	(0.017)	(0.008)	(0.017)
Q1	0.544	0.831	0.027
	(0.014)	(0.008)	(0.013)
Q2-Q1	0.036	0.02	0.096
	(0.016)	(0.011)	(0.021)

Note: The table contains estimated potential completion rates (Y^1) and value added ($Y^1 - Y^0$) with standard errors in parentheses. The endogenous variable is program enrollment in the year of application. Standard errors are clustered by program and year. Models are estimated for program and college completion using 2SLS.

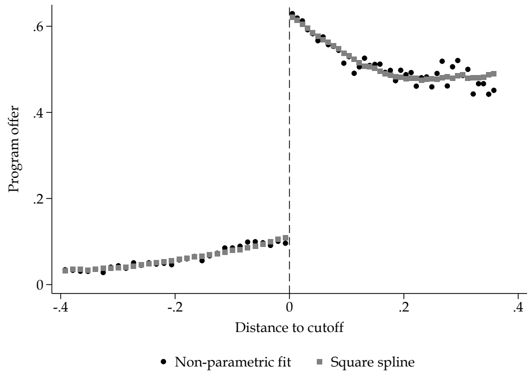
Table B4: Average completion gaps across programs

	Program, Y^1	College, Y^1	College, $Y^1 - Y^0$
Gap in pooled model	0.031	0.016	0.064
Average gap across programs	0.006	-0.001	0.073

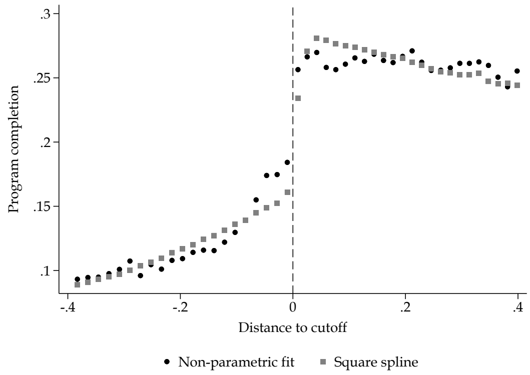
Note: The table displays the gaps in program completion rate, college completion rate, and college completion value added. The first row reproduces the main results of Table 4. The second row displays the corresponding means of program-level estimates. Program-level estimates are estimated by interacting program dummies with admission and instruments. Appendix figure B5 shows the distributions of program level gaps.



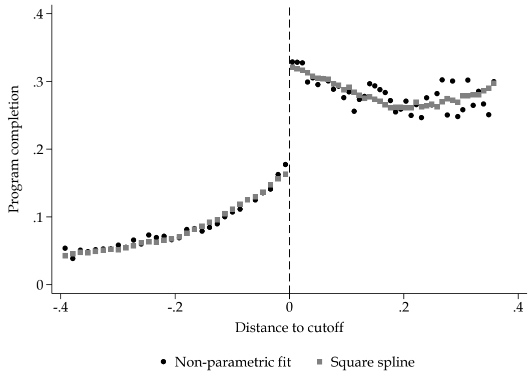
(a) Admission, Quota 1



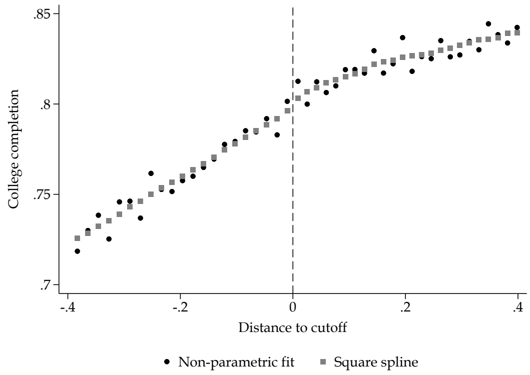
(b) Admission, Quota 2



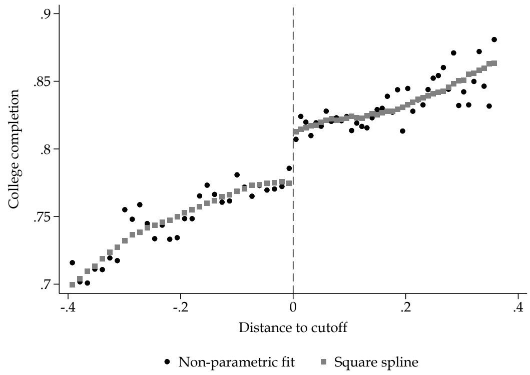
(c) Program completion, Quota 1



(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.

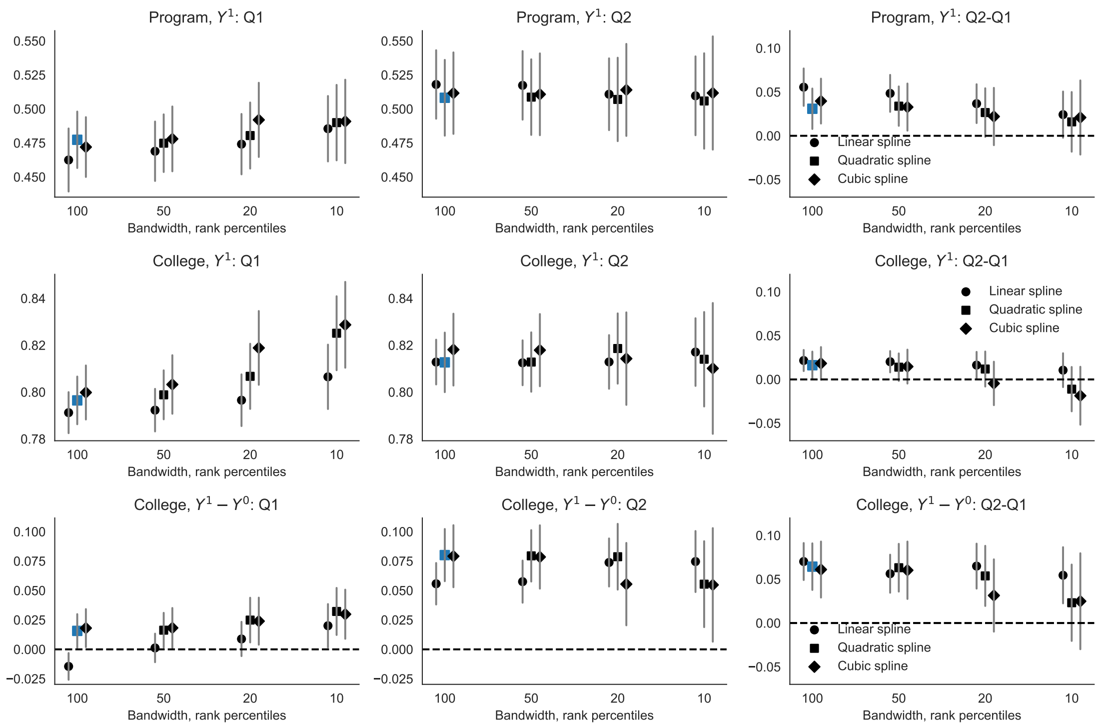


Figure B4: RDD estimates with varying bandwidth and specification

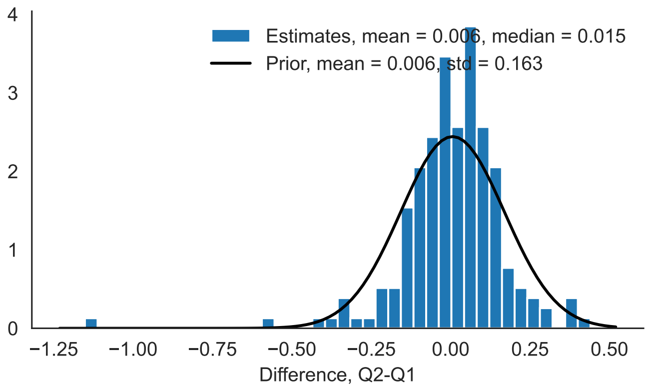
Note: The figure shows parameter estimates and 95-percent confidence bands for RDD estimates with varying bandwidth on the x-axis and different orders of the polynomials in the running variables. The baseline estimates are shown in blue squares.

Table B5: Change in Quota 2 share by field and select

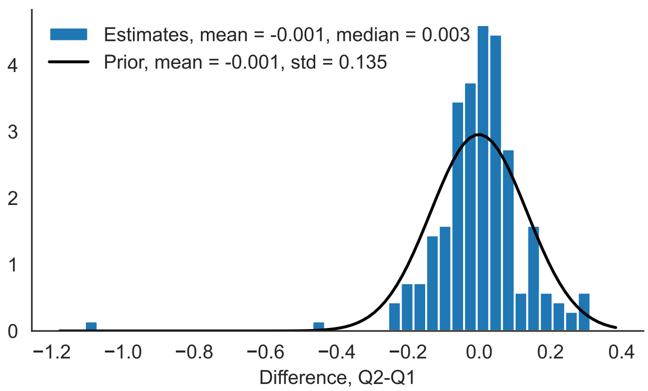
	Change in Quota 2 size after lifting restriction											
	[-2-.01)			[.01,.10)			.10-			Total		
Academic field	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Health	11	19.0	91.7	1	2.7	8.3	0	0.0	0.0	12	10.9	100.0
Humanities	25	43.1	54.3	16	43.2	34.8	5	33.3	10.9	46	41.8	100.0
Social science	10	17.2	32.3	12	32.4	38.7	9	60.0	29	31	28.2	100.0
STEM	12	20.7	57.1	8	21.6	38.1	1	6.7	4.8	21	19.1	100.0
Total	58	100.0	52.7	37	100	33.6	15	100	13.6	110	100.0	100.0

	Change in Quota 2 size after lifting restriction											
	[-2-.01)			[.01,.10)			.10-			Total		
Selectivity	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Very low	0	0.0	0.0	1	2.7	100.0	0	0.0	0.0	1	0.9	100.0
Low	6	10.3	46.2	4	10.8	30.8	3	20	23.1	13	11.8	100.0
Moderate	37	63.8	55.2	22	59.5	32.8	8	53.3	11.9	67	60.9	100.0
High	15	25.9	51.7	10	27	34.5	4	26.7	13.8	29	26.4	100.0
Total	58	100.0	52.7	37	100.0	33.6	15	100.0	13.6	110	100.0	100.0

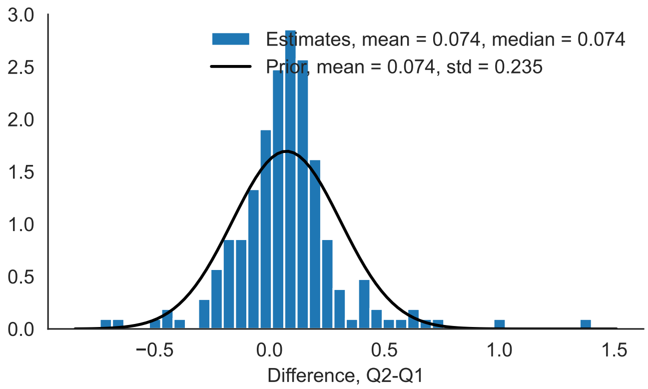
Note: The table displays the number of academic programs by the change in Quota 2 share after the restriction is lifted by field and selectivity.



(a) Program, Y^1



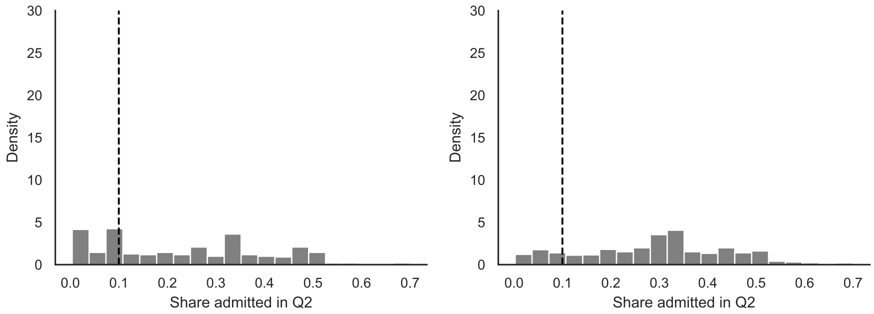
(b) College, Y^1



(c) College, $Y^1 - Y^0$

Figure B5: Distribution of program level estimates

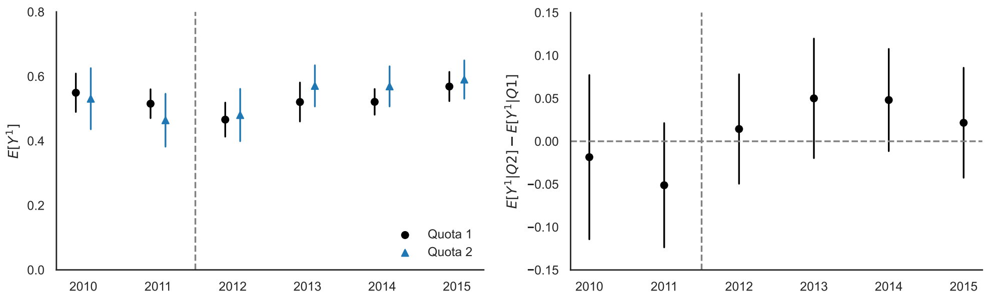
Note: The figure shows means and standard deviations of program-level estimates. Program level estimates are estimated by interacting program dummies with admission and instruments. Standard errors for the estimates are clustered by program. Following Kline, Rose, and Walters (2022), we estimate the variance of the distribution of program level estimates by $\frac{1}{P}\sum_{p=1}^{P}((\widehat{\beta}_p - \overline{\widehat{\beta}}_p)^2 - s_p^2)$, where $\widehat{\beta}_p$ is the gap for program p, $\overline{\widehat{\beta}}_p$ is the average gap and s_p is the standard error of $\widehat{\beta}_p$. Normal distributions are calibrated using the estimated means and standard deviation.



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

Figure B6: 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) Non-academic programs, levels (b) Non-academic programs, difference

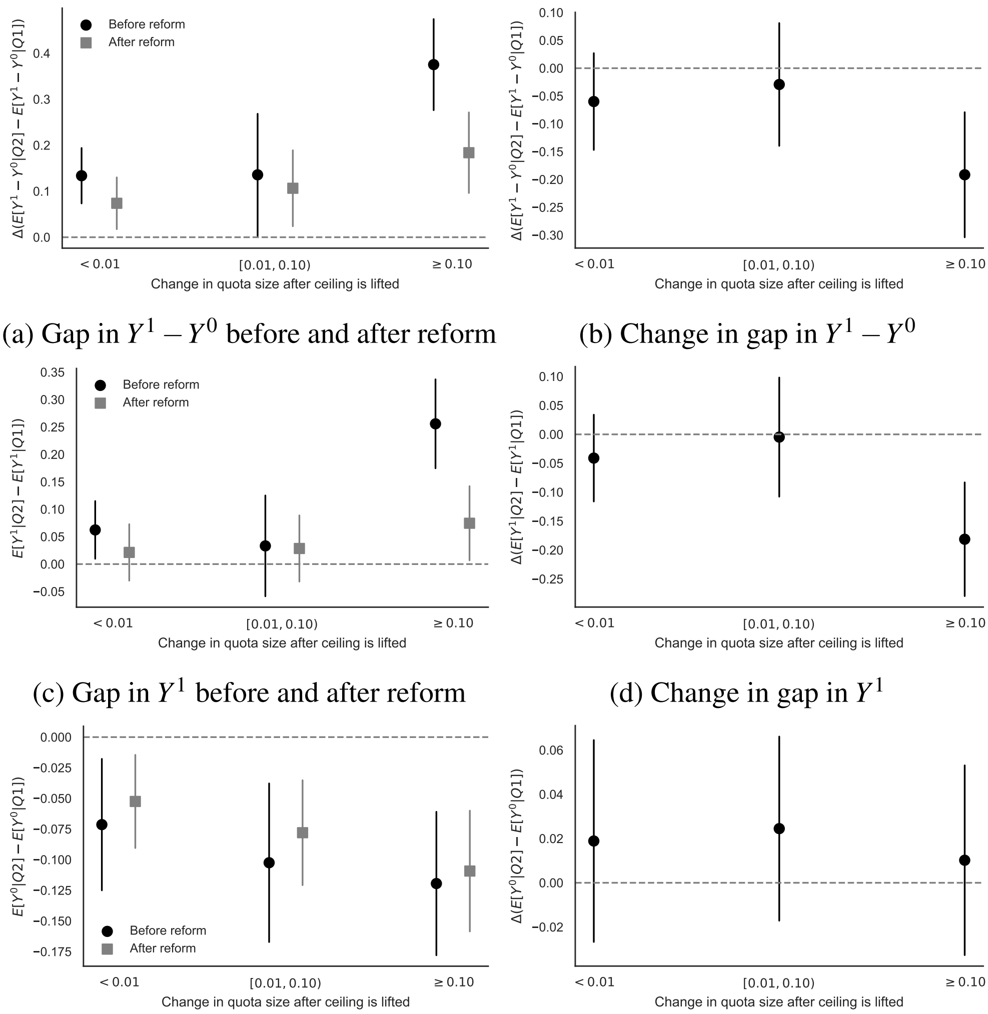
Figure B7: Completion rate of marginal applicants, non-academic programs

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.

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

	Completes program (Y^1)	Completes college (Y^1)	Completes college ($Y^1 - Y^0$)
(.15,.4] vs ≤.15	0.003 (p=0.916)	-0.010 (p=0.610)	-0.034 (p=0.289)
>.4 vs ≤.15	0.038 (p=0.244)	-0.008 (p=0.736)	-0.045 (p=0.235)
>.4 vs (.15,.4]	0.035 (p=0.238)	0.001 (p=0.949)	-0.012 (p=0.741)

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



(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

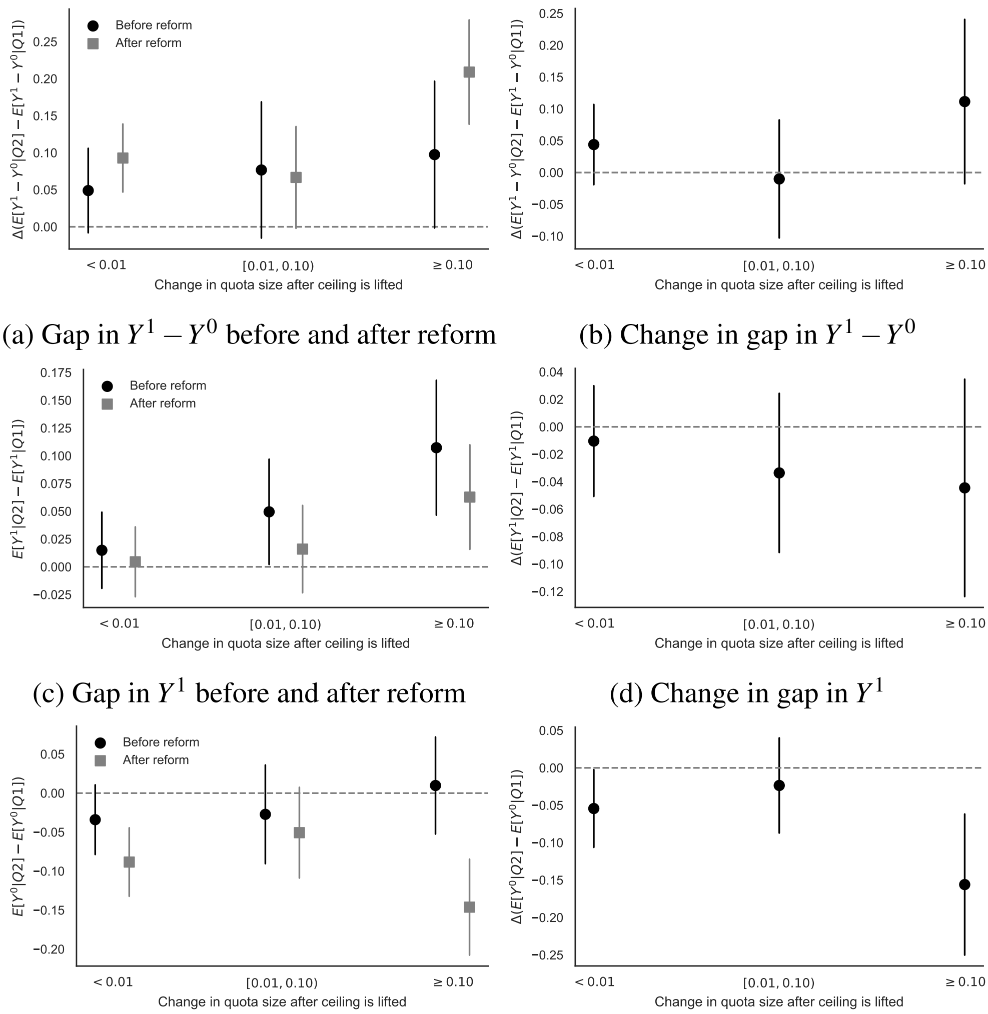
Figure B8: Program completion gap by intensity of constraint and before and after reform

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.

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

	Completes program (Y^1)	Completes college (Y^1)	Completes college ($Y^1 - Y^0$)
Low vs Very low	-0.009 (p=0.849)	0.064 (p=0.139)	0.019 (p=0.860)
Moderate vs Very low	0.015 (p=0.760)	0.102 (p=0.016)	0.102 (p=0.342)
High vs Very low	0.030 (p=0.585)	0.089 (p=0.048)	0.133 (p=0.218)
Moderate vs Low	0.024 (p=0.350)	0.038 (p=0.044)	0.083 (p=0.013)
High vs Low	0.039 (p=0.271)	0.025 (p=0.301)	0.114 (p=0.002)
High vs Moderate	0.015 (p=0.670)	-0.013 (p=0.573)	0.031 (p=0.347)

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



(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 B9: 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 B8: Test of differences in completion gaps by program characteristics: Criteria

	Completes program (Y^1)	Completes college (Y^1)	Completes college ($Y^1 - Y^0$)
Grades vs Essay	-0.014 (p=0.056)	0.001 (p=0.805)	0.011 (p=0.079)
Interview vs Essay	0.037 (p=0.238)	-0.007 (p=0.801)	-0.012 (p=0.697)
CV vs Essay	-0.015 (p=0.023)	-0.005 (p=0.214)	0.004 (p=0.528)
Test vs Essay	0.027 (p=0.443)	0.012 (p=0.676)	0.030 (p=0.370)
Interview vs Grades	0.051 (p=0.103)	-0.008 (p=0.762)	-0.023 (p=0.441)
CV vs Grades	-0.001 (p=0.746)	-0.006 (p=0.014)	-0.008 (p=0.033)
Test vs Grades	0.041 (p=0.232)	0.011 (p=0.699)	0.019 (p=0.569)
CV vs Interview	-0.052 (p=0.091)	0.001 (p=0.955)	0.015 (p=0.602)
Test vs Interview	-0.010 (p=0.725)	0.019 (p=0.172)	0.042 (p=0.073)
Test vs CV	0.042 (p=0.215)	0.017 (p=0.540)	0.026 (p=0.420)

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 program-year-level. Details are described in the note to Figure 8.

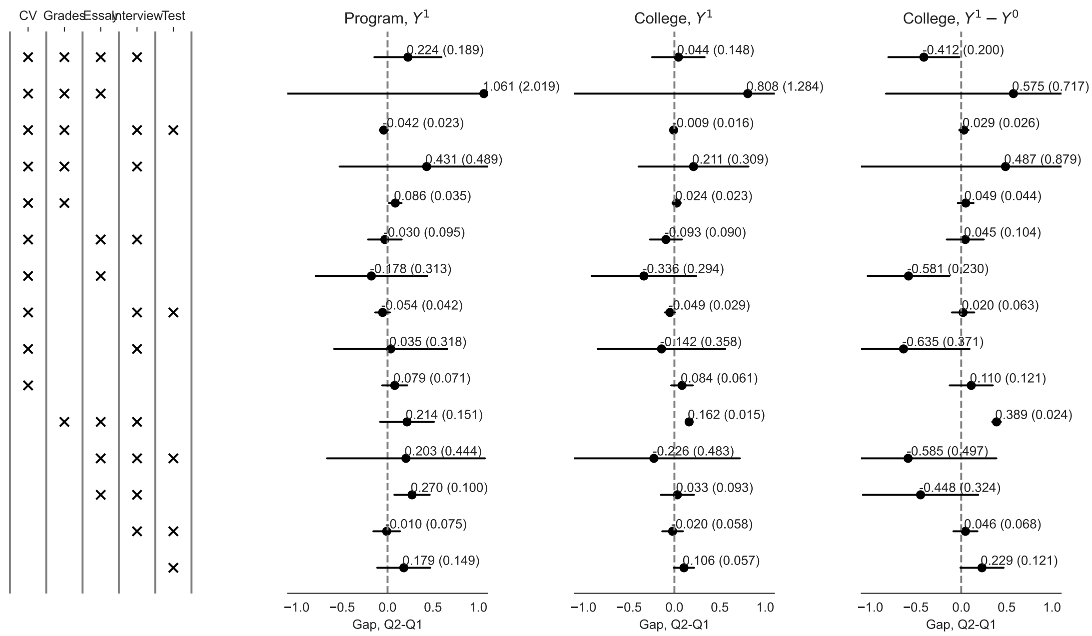


Figure B10: Difference in completion rates and value added, Holistic - GPA, by criteria

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

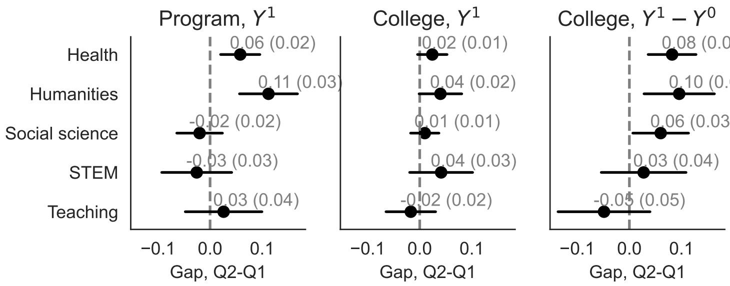


Figure B11: Difference in completion rates and value added, Holistic - GPA, by field

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.

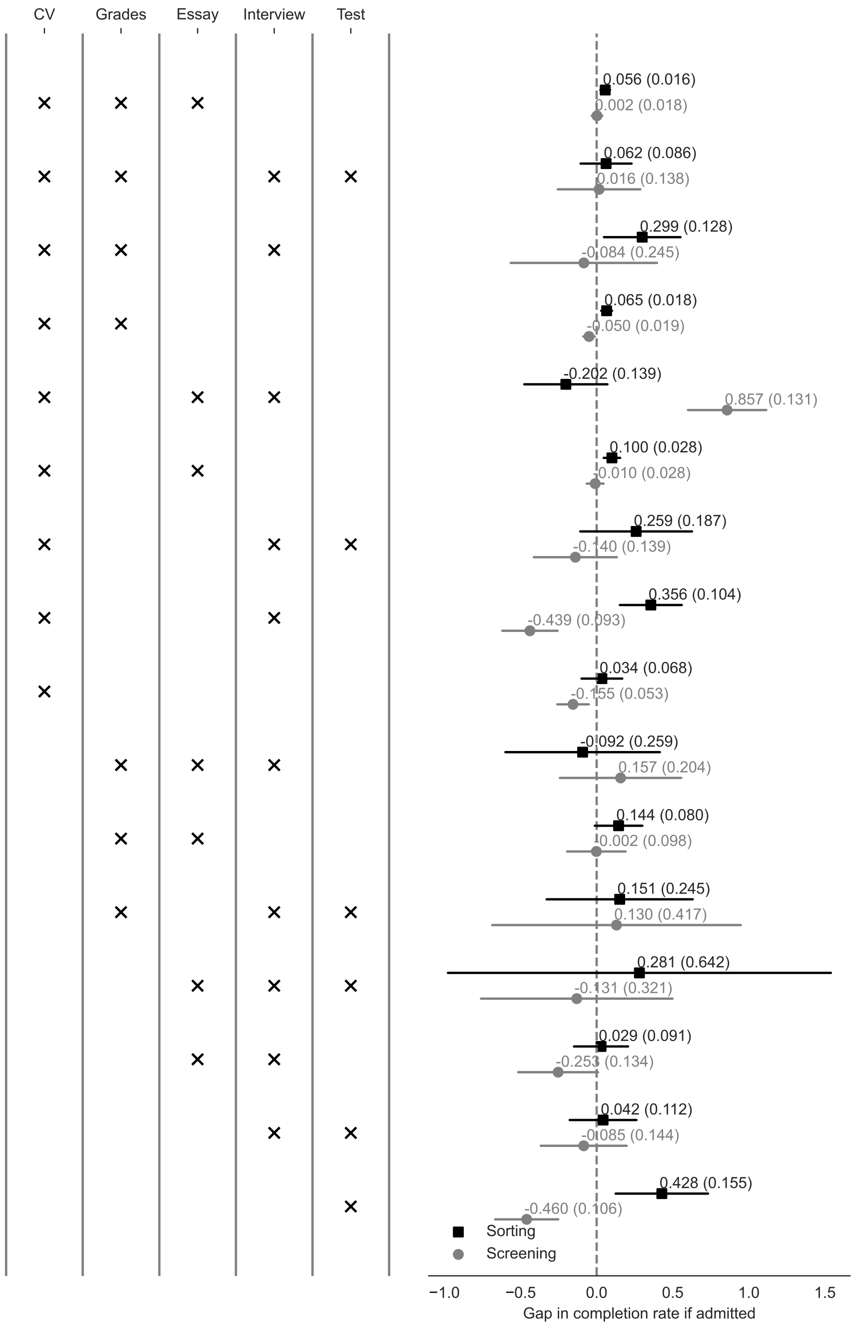


Figure B12: Decomposition, by criteria combination

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

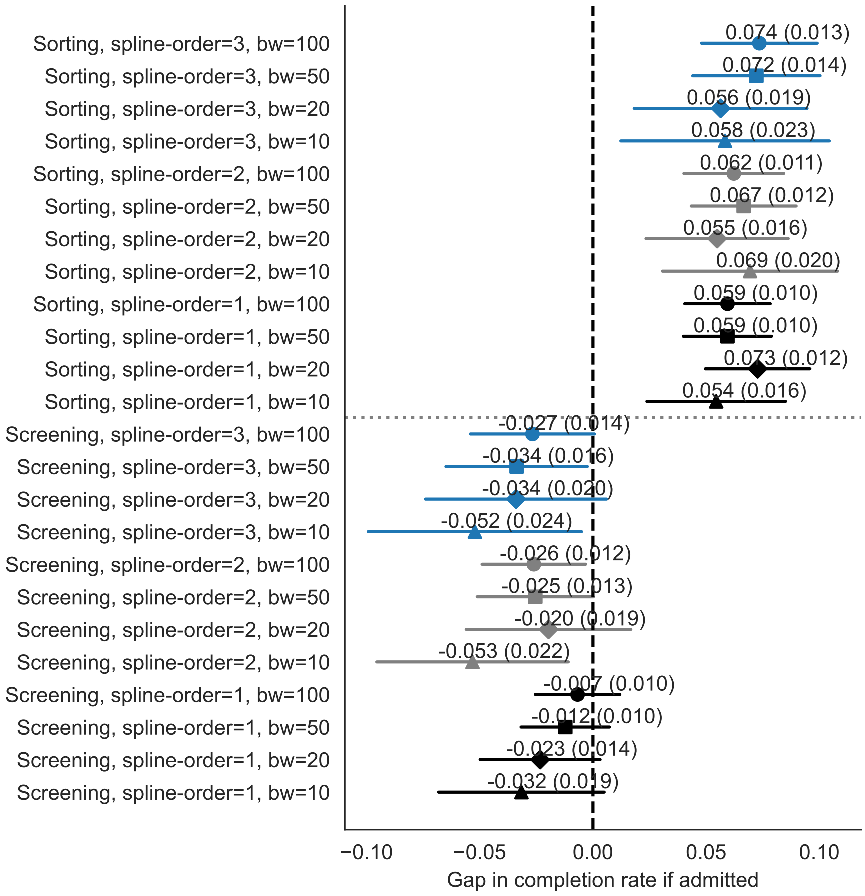


Figure B13: Decomposition, robustness checks

Note: Decomposition estimates of the screening and sorting decomposition in equation (7) for subsets of programs by criteria combination. The method is described in the note for Figure 9.

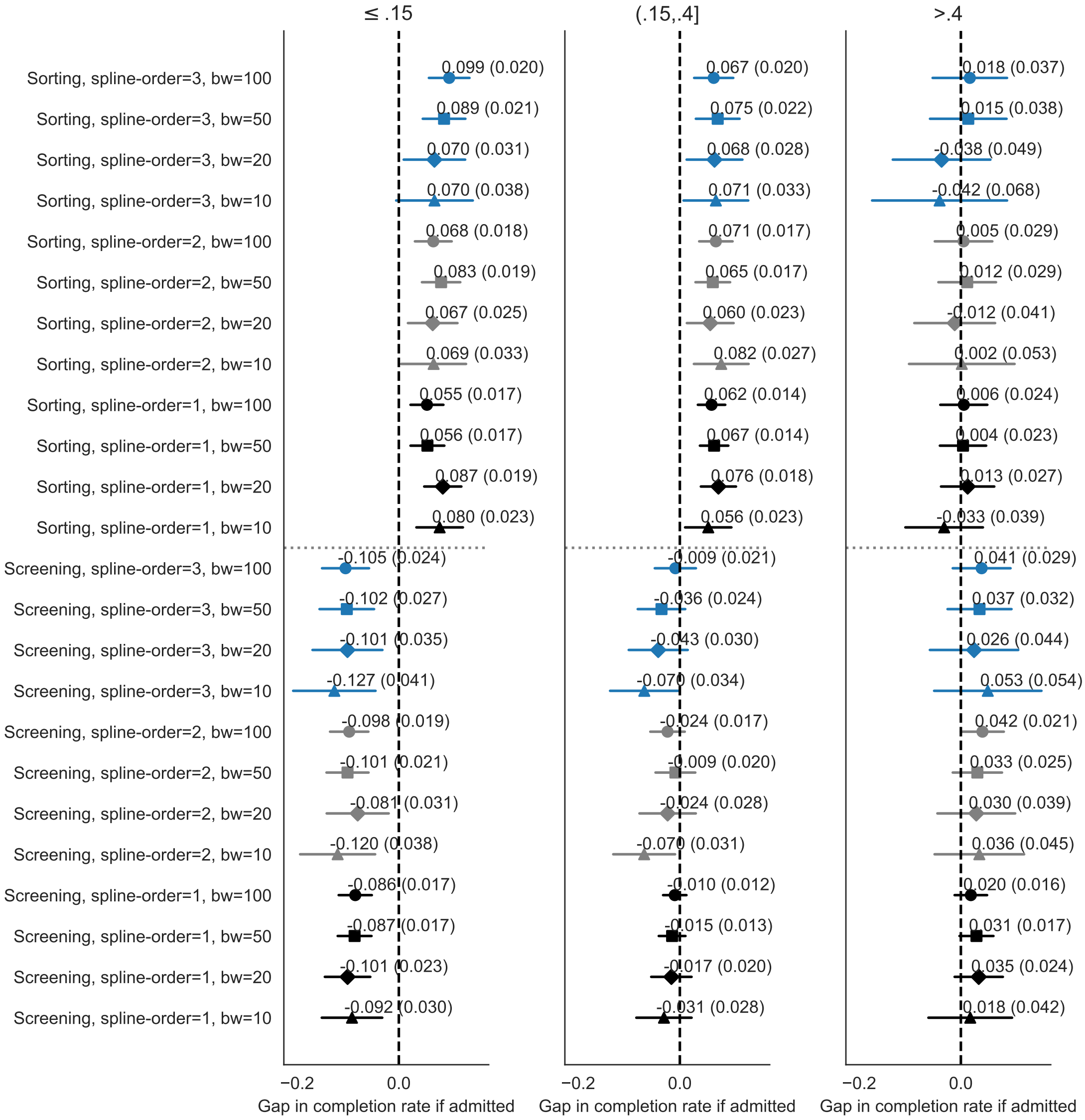


Figure B14: Decomposition by importance of Quota 2, robustness checks

Note: The figure shows parameter estimates and 95-percent confidence bands for decomposition estimates with varying bandwidth on the x-axis and different orders of the polynomials in the running variables

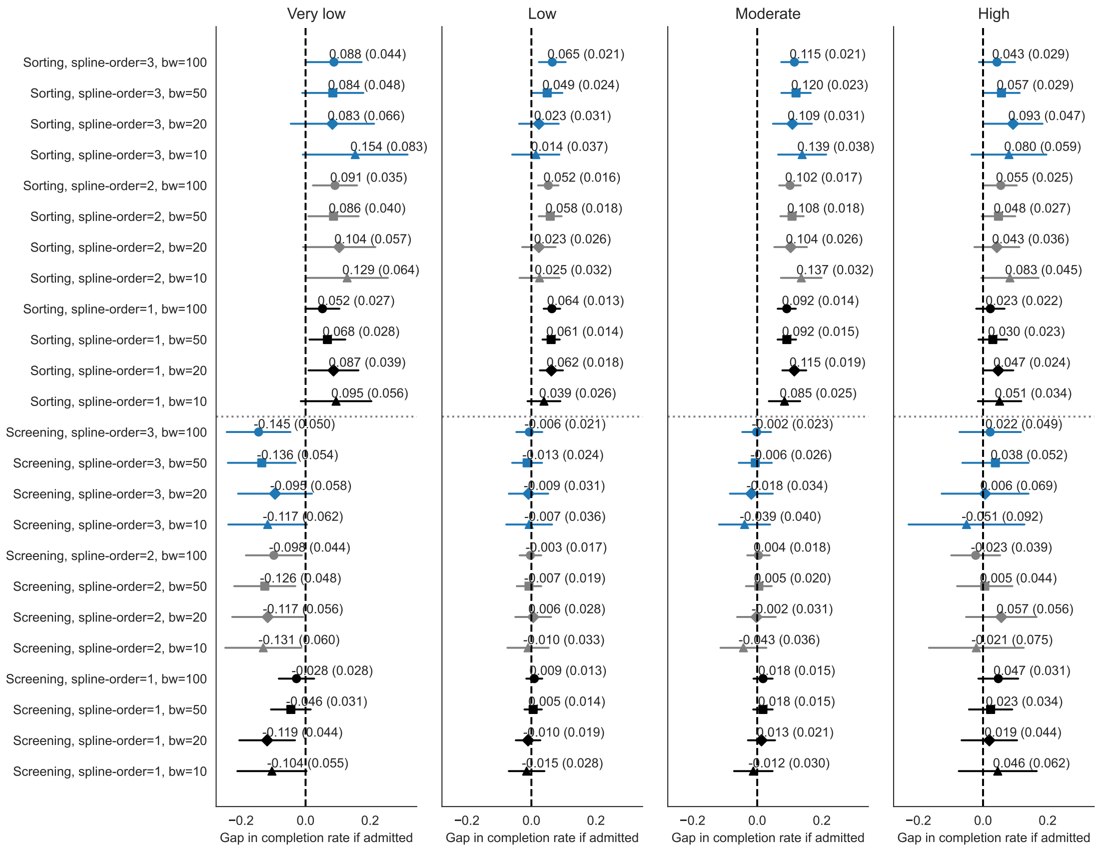


Figure B15: Decomposition by selectivity, robustness checks

Note: The figure shows parameter estimates and 95-percent confidence bands for decomposition estimates with varying bandwidth on the x-axis and different orders of the polynomials in the running variables

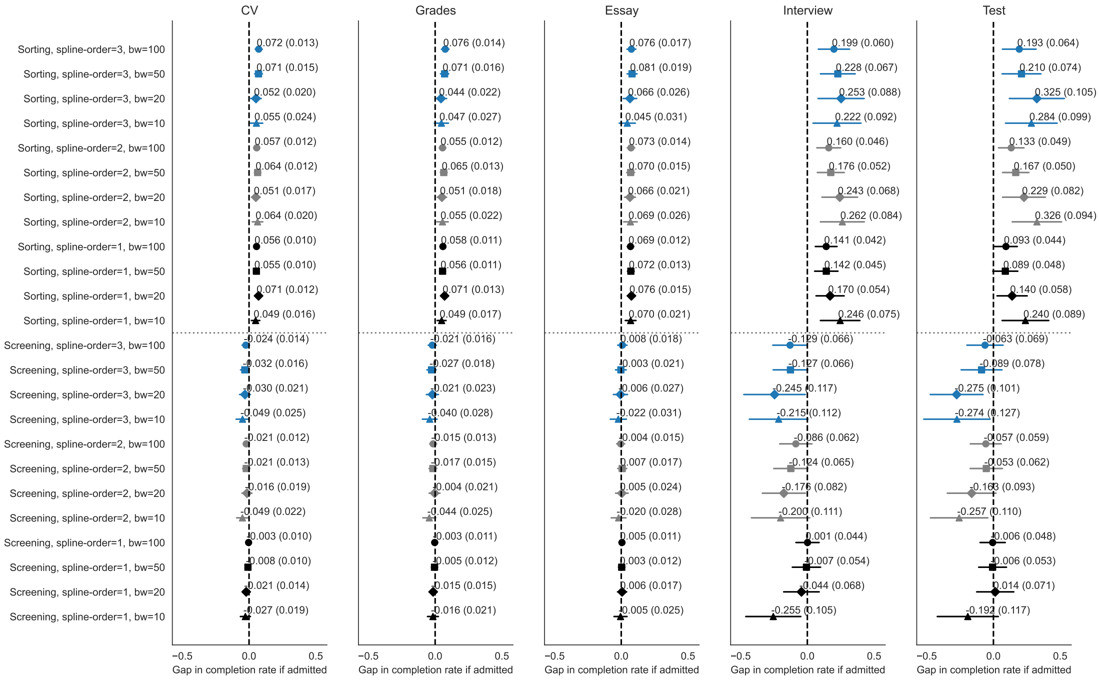


Figure B16: Decomposition by criteria used, robustness checks

Note: The figure shows parameter estimates and 95-percent confidence bands for decomposition estimates with varying bandwidth on the x-axis and different orders of the polynomials in the running variables

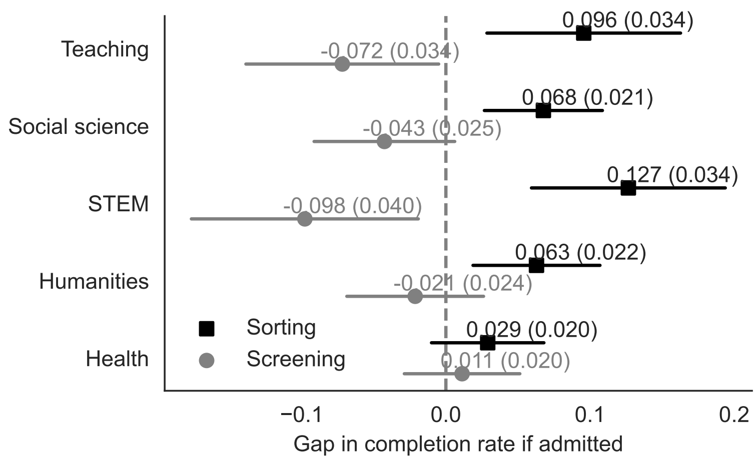


Figure B17: Sorting and screening decomposition of across-quota marginal program completion gap by field

Note: Decomposition estimates of the screening and sorting decomposition in equation (7) for subsets of programs by field. The method is described in the note for Figure 9.

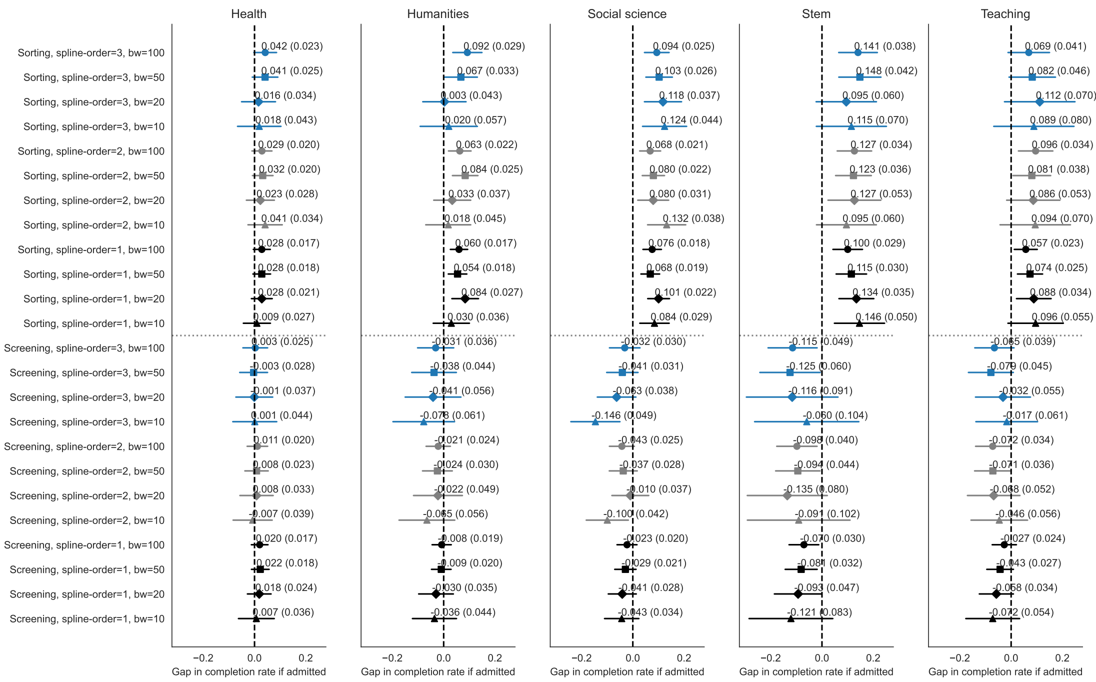


Figure B18: Decomposition by field, robustness checks

Note: The figure shows parameter estimates and 95-percent confidence bands for decomposition estimates with varying bandwidth on the x-axis and different orders of the polynomials in the running variables