Asymmetric Information in Matching Markets: Evidence from Medical School Programs in Denmark*

Benjamin U. Friedrich† Martin B. Hackmann‡ Adam Kapor§
Sofia Moroni¶ Anne Brink Nandrup‖

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Abstract

This paper studies asymmetric information in a matching market and how market participants strategically adjust to this situation. We study these questions in the market for medical school programs in Denmark, which assigns students to programs based on a centralized assignment mechanism. Using administrative data on student preferences, college priorities, and student outcomes, as well as exploiting an information experiment, we present evidence that students and rival programs hold payoff relevant information that would, if known by the program, allow the program to admit students with lower program dropout rates. Building on these insights, we estimate an empirical model of this matching market that allows for heterogenous program and student preferences as well as two sources of interdependent values: student self-selection and interdependent program values. We use the estimated model to quantify the relative importance of these two mechanisms and to simulate how alternative information structures affect the allocation in this market.

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†Northwestern University, Kellogg School of Management
‡UCLA, Department of Economics, CESifo, and NBER
§Princeton & NBER
¶University of Pittsburgh
‖VIVE Denmark

1 Introduction

Matching is a key function of markets, including labor, college, marriage, ride- and home-sharing markets. Which matches are formed under a given mechanism, and which market designs are effective at forming high-value matches, depend crucially on the information structure of the market participants. In many settings, market participants may not know their own preferences. For instance, a college program collects information about the ability and motivation of a prospective student through interviews and recommendation letters which likely leave some residual uncertainty about the applicant's qualities. If the program could observe how well the applicant interviewed at rival programs, or what the applicant knows about his own motivation, it would revise its assessment of the candidate and perhaps its optimal decision. When this is the case—that is, when students' and rival programs' private information are relevant to programs' payoffs—we say that the information structure exhibits interdependent values.

Several important matching markets are organized through centralized clearinghouses (Roth, 2008). However, the theoretical case for centralized stable matching mechanisms assumes that agents on both sides know their own preferences (Gale and Shapley, 1962; Roth and Sotomayor, 1992), although they may be uncertain about the other side's (Roth, 1989). Empirical work in two-sided matching markets typically assumes that agents know their own preferences as well (Sørensen, 2007; Fox et al., 2012; Agarwal, 2015).

In this paper, we provide the first empirical evidence of interdependent values in a matching market and of market participants' strategic reactions to this situation. We do so in an empirically important sector: the training of doctors in Denmark. We characterize the admission strategies of medical school programs and the application strategies of students, allowing for two sources of interdependent values: interdependent program values and student self-selection on unobserved preferences. Using rich administrative data from Denmark, we find evidence of both channels. This suggests that programs benefit from learning information rival programs hold as well as learning about student preferences in identifying students with higher completion rates.

Our analysis sheds new light on the market design tradeoffs inherent to the assignment of students to programs, a process which follows different protocols across countries. While many European countries use a centralized clearinghouse, the U.S. uses a decentralized mechanism. Decentralized early college admissions may reveal relevant information on student preferences (Avery and Levin, 2010) or reduce the winner's curse from admitting students who were rejected by rival programs in the context of interdependent program values (Lee, 2009). On the other hand, early contracting in a decentralized process may lead to conges-

tion (Roth and Xing, 1997) or stop the information disclosure process too early and thereby result in allocative inefficiencies in matching. An extreme case for this is provided in the unraveling of decentralized matching market of doctors to residency programs in the U.S., which then prompted the introduction of a centralized clearinghouse in 1954, called the "match", see Roth (2008) for a discussion.

We investigate these questions in the important context of Danish medical school programs, which have program non-completion rates of up to 20%, despite drawing from the highest caliber high school graduates. Our setting is well suited to study the information structure of a matching market for a variety of reasons. First, we have rich administrative data on the universe of applications, admissions, and enrollment. Matching takes place via a centralized deferred acceptance procedure, and we observe student preference rankings over programs, and college rankings over students, that are submitted to the mechanism, in addition to students' post-match outcomes such as dropout and completion rates. We are not aware of a different setting that provides information on all of these variables.

Second, we can take advantage of key institutional details to disentangle program's information from student selection. Specifically, students are admitted based on two quotas: quota 1 and quota 2. Quota 1 students are admitted purely on the basis of the student's high school GPA, a variable that is commonly observed by the econometrician and all market participants. In contrast, quota 2 applicants must prepare additional application materials, and are admitted based on the program's assessment of cognitive skills, motivation, and experience, which the program elicits from motivation letters, extra-curricular activities, and interviews in the case of some programs.

Third, we are able to combine information on student preferences with an information experiment in our sample period to test for interdependent values, as we detail below.

We start our analysis by presenting descriptive facts on the admission and applicant preferences as well as the information structure. Using a regression discontinuity design, we compare dropout rates between quota 1 and quota 2 students at the GPA cutoff. We find a significantly lower dropout rate among quota 2 admissions, which suggests that the quota 2 screening process reveals additional information on program completion and that programs act on this information in their admission decisions. Likewise, we find that students admitted based on their GPA have lower dropout rates if they also applied via quota 2. This suggests that students self-select based on motivation into the quota 2 applicant pool, which then predicts dropouts.

We then turn to the information experiment to test for interdependent values. In 2002, the University of Southern Denmark at Odense, henceforth Odense, refined their screening of quota 2 applicants in an effort to lower their dropout rates. Specifically, the program

added a knowledge test and a personal interview. Using a difference-in-differences design that compares Odense to their closest competitor Aarhus before and after the reform, we find that the reform led to a decrease in Odense's dropout rate of 6.7 percentage points. In contrast, the reform led to an adverse selection of students at Aarhus. Specifically, we see a 12 percentage point increase in dropout rates among students who prefer Odense but are admitted to Aarhus in the post-reform period. The findings are consistent with interdependent program values that imply a winner's curse at Aarhus as Odense increases its screening precision. The findings are also potentially consistent with changes in student self-selection, if the revised review process increases the application costs borne by students. If so, less motivated students may apply via quota 2 at Aarhus instead of Odense, which may contribute to the dropout patterns when preferences are correlated with dropout outcomes. Either way, our evidence demonstrates that Aarhus could lower their program dropout rates by conditioning on information held by Odense and students, resulting in an information structure of interdependent values.

While programs in our setting cannot condition their decisions on students' rankings, they may condition on the students' former address, which we show is a strong predictor of their rankings. Given that students tend to prefer nearby colleges, a program evaluating an applicant from its rival's home region understands that this student is likely to be applying as a second choice, and that the student is more likely to accept the distant offer in the event that the student's local program rejects him.

Programs can mitigate the winner's curse and take advantage of student self-selection by strategically favoring local students over students from the rival region. When the program's own signals become more informative, the incentive to favor locals decreases. In contrast, when rejection by a rival is more informative, there is greater reason to favor locals. We find some evidence to support this. Odense weakens its bias towards locals in the post-reform period as it becomes better at screening applicants. However, we do not find evidence that Aarhus strengthens its home bias to mitigate the adverse consequence of Odense's admission experiment.

Building on these observations, we then provide a formal characterization of the admission and application decisions under interdependent values when matches are formed based on a student-proposing deferred acceptance mechanism (DA). We develop sufficient conditions under which admission decisions can be characterized by cutoff policies and characterize the cutoff rule. We then estimate a parameterized version of the theoretical model. The purpose of the empirical model is to quantify the information structure more precisely, to distinguish between student self-selection and interdependent program values, and to evaluate counterfactual assignment mechanisms. On the student side, we model imperfect information about

talents, preferences over programs, and the quota 1 and quota 2 application decisions, where the latter depends on preferences, application costs, and admission chances. On the program side, we model private signals, programs' quota 2 admission cutoffs, and student dropouts. We model heterogeneity in student observables, including GPA and their former region of residence and allow for affiliation between unobserved program signals, student talents, and student preference shocks. Programs' payoffs depend on students' propensity to drop out and on other factors which may vary with observables.

We use data from before and after the reform, allowing the precision of programs' signals, the cost to students of quota-2 applications, and the (endogenous) admissions cutoffs to vary between the pre- and post-reform periods, while holding students' and programs' underlying preferences and the parameters governing the dropout process fixed. We estimate the model via generalized method of moments (GMM), using the sequential E-M algorithm proposed by Arcidiacono and Jones (2003).

Our preliminary estimates suggest that Odense's program signal carries information on student talents both in the pre- and the post-reform. The precision is relatively low in the pre-reform period but increases significantly after the reform. We estimate a post-reform correlation of about 19% between the program's signal and unobserved student talent on average, up from 6% in the pre-reform period. Talents are positively correlated between programs, giving rise to interdependent program values. We estimate a correlation of 79%. On the student side, we estimate that preferences are correlated with talents as indicated by a correlation of 27-47%. We also estimate a significant increase in quota 2 application costs for Odense in the post-reform period. This suggests that quota 2 application costs provide an instrument for market signaling in the spirit of Spence (1973). Overall, our model reconciles the change in dropout rates at Odense and Aarhus following the information experiment through a combination of interdependent values and student selection. Building on these insights, we intend to simulate alternative mechanisms, including changes in application costs, program signal sharing, and the role of student preference signaling.

Our analysis is connected to several strands in the literature. First, our analysis is connected to the literature on matching markets. Starting with the pioneering work by Gale and Shapley (1962), a large literature has studied the existence and properties of stable matching mechanisms. Methodologically, we build on cutoff representations of matchings (Azevedo and Leshno, 2016) as well as on tools from the auction theory (Milgrom and Weber, 1982).

A recent literature has provided extensions of stability, and investigated the existence of stable matchings, in settings with incomplete information (Chakraborty et al., 2010; Liu et al., 2014). We pursue an alternative approach, conceptually closer to Chade et al. (2014),

who develop a model of college admissions with common values in a decentralized setting with many agents. We consider the game induced by a centralized student-proposing DA algorithm, which plays a key role in college markets outside the U.S., as well as assignment to public schools within the U.S.[1]. In their model, as in ours, equilibria involve ex-post regret for some agents, and do not satisfy stability.

A novel feature of our model is that students have observables which provide public information about their preferences, as well as private information about their preferences and private signals observed by programs. We develop conditions under which the programs' optimal admission rule can be characterized by a cutoff in the program's private signal which varies as a function of commonly-observed variables such as GPA and location. We then estimate this cutoff function in our data.

Second, we contribute to the literature on matching markets with imperfect information. Most studies assume complete information with a few exceptions.[2] Che and Koh (2016) show that colleges in a decentralized market that are subject to aggregate demand shocks should favor students whom they like for idiosyncratic rather than common reasons. Friedrich (2020) studies the role of imperfect information on matching between managers and firms. Firms learn superior information about their internal candidates relative to the market, which intensifies competition for young talent and leads to adverse selection among external managerial hires. Most closely to our analysis are two applied theory papers on early college admissions in the U.S. Avery and Levin (2010) argue that early admission programs give students an opportunity to signal their fit for a particular college, which directly enters colleges' preferences. Lee (2009) argues that screening on preferences allows programs to reduce the risk of a winner's curse by reducing the risk of admitting students that were rejected at their preferred program. We contribute to these studies by incorporating both channels, which we refer to as student self-selection and interdependent values, in an important matching setting. To the best of our knowledge, we are the first to estimate how market participants strategically adjust to these sources of interdependent values in a matching market.

Third, and more broadly, our analysis sheds light on market design in settings with interdependent values and is thereby connected to settings in which agents do not necessarily know their preferences, including important matching markets, such as education, labor, ride-sharing and home-sharing markets, auction markets (Milgrom and Weber, 1982),[3] and

[1]The DA algorithm has replaced existing mechanisms on the placement of students to public schools in NYC (Abdulkadiroğlu et al., 2005a) and Boston (Abdulkadiroğlu et al., 2005b)

[2]Empirical studies on matching markets with complete information include Sørensen (2007), Fox et al. (2012), and Agarwal (2015). Larroucau and Rios (2020) considers college admissions in Chile with incomplete information on the student side, where students may learn their match-quality after enrollment.

[3]A recent empirical study on the implications of interdependent values in auction markets is Compiani

markets that may suffer from inefficiencies arising from adverse selection, including insurance and credit markets. While some of the aforementioned markets are ones with frequent interactions in which reputation mechanisms can improve efficiency, our setting is one with relatively few interactions. As such our findings relate more closely to the efficacy of screening and signaling efforts to reduce information asymmetries (see Kawai et al. (2020) for a literature discussion).

The remainder of the analysis is organized as follows. Section 2 describes important institutional details of our setting. Section 3 describes our conceptual framework and characterizes the application and admission strategies. Sections 4 and 5 describe the data and present direct evidence on the information structure of the game. In Section 6, we develop the empirical model of our conceptual framework. We discuss the estimation strategy and the results in Section 7. Finally, we conclude with a discussion of our findings and potential counterfactual exercises in Section 9.

2 Institutional Background

We focus our empirical analysis on medical school programs in Denmark. The training program is five years long and students can apply for medical school programs right after completing their high school education. After completing the final medical exams, medical doctors also have to complete one year of practical clinical education and one year wich is introductory to the speciality. To become specialists (including general practitioners), doctors have to undergo an additional 5 years of specialty training, see Olejaz et al. (2012) for details. Below we discuss the admissions process to medical school programs in further detail, before describing the data collection.

2.1 University Applications and Admissions

Upon completion of upper secondary education (high school education), students can apply to university programs. All university applications are handled through a centralized admission system, organized by the Danish Central Admissions Secretariat (CAS). As in most European countries, Danish students apply to *programs*. A program denotes a field of study (e.g. medicine) at a specific institution (e.g. University of Copenhagen).

Each program has a fixed capacity of seats. These seats are divided into two categories, quota 1 and quota 2, that have distinct admission criteria. Quota 1 seats are allocated purely on the grounds of the applicants' high-school GPA. In contrast, and as we detail below, quota 2 seats are granted to applicants who do not meet the GPA requirements. Instead, quota 2 seats are allocated based on a broader set of characteristics, including the

et al. (2020).

program's assessment of the applicants' cognitive skills, motivation and past experience. Details of the administration and scoring of the quota 2 admission criteria differ across programs. Medical programs have their own quota 2 assessment committees and typically evaluate applicants based on their motivational letter, extra-curricular activities (mainly work-experience, volunteering, exchange experience and additional academic qualifications), as well as potentially additional tests and interviews. Programs cannot use the student's preference ranking, which we observe as detailed below, in their rank-order over students.

During our sample period, universities determined the maximum number of students that can be admitted to a given program prior to the period of application. The exceptions are Medicine, Dentistry and Veterinary, where the number of seats are regulated by a government agency to meet the future public demand of health care professionals (e.g. physicians). Programs determine the fraction of college seats that are assigned to quota 1 and quota 2 in March-April, subject to national higher education regulation, which we return to below.[4]

2.2 Rankings and the Deferred Acceptance Algorithm

Quota 2 applications are due in mid-March and quota 1 applications are due in early July. The quota 1 application entails an ordinal ranking of the student's (up to) 8 most preferred programs. Only programs listed in this ranking are considered by CAS. Hence, to be considered by CAS, every quota 2 application must be accompanied by a quota 1 application, but not vice versa. In total a student can apply to at most 8 distinct programs and submit a total of up to $8+8=16$ program-by-quota student applications if the students has applied to all 8 programs via quota 2 as well. In our setting, 99% of applicants list 7 or fewer programs in their quota 1 application.

Rankings: CAS treats the different admission quotas as separate "pseudo"-programs and combines a student's quota 1 and 2 applications into a pooled rank-order list. The pooled rank-order list maintains the reported preference order across programs but prioritizes quota 1 applications over quota 2 applications within a program. Specifically, if a student applied to program j via quota 2, then the quota 2 application is considered right after the quota 1 application for that program j in this extended rank-order list. For example, suppose that student i applied to programs $4, 7, 2$ and 5 via quota 2 and submitted the quota 1 rank-order list is $l_i = \{4, 3, 7, 2, 5\}$, where the numbers correspond to distinct programs. The extended program ranking is then $l_i^{ext} = \{4^{Q1}, 4^{Q2}, 3^{Q1}, 7^{Q1}, 7^{Q2}, 2^{Q1}, 2^{Q2}, 5^{Q1}, 5^{Q2}\}$, where $Q1$ denotes a quota 1 application and $Q2$ denotes a quota 2 application.

Programs rank student applicants within each quota. Quota 1 applicants are ranked

[4] In 2001 the regulation decreased the share of quota 2 seats to a maximum of 25% of capacity, and in 2008 this was further reduced to 10%.

passively based on their GPA. Programs also rank their quota 2 applicants and assign an applicant score based on the criteria mentioned above. Below we present more details on the scoring function for medical school applicants to Odense.

Deferred Acceptance Algorithm: Finally, the pooled rank-order lists and the program rankings (by quota) are used as inputs to a program-proposing deferred acceptance algorithm that matches applicants to programs. If the number of applicants exceeds the number of quota 1 seats, admission through quota 1 is restricted and students whose high school GPA falls below the program- and year-specific GPA cutoff will not receive an offer of admission via quota 1. Medicine programs typically also maintain a quota 1 stand-by list. This list assigns vacated seats, as some students decide not to enroll, to the next best applicants that indicated a preference for stand-by seats in their application. The stand-by list effectively has a lower GPA cutoff and grants the students above the cutoff automatic admission either in the current academic year if seats become available (this applies to about one-third of standby admissions), or in the following year if the student submits an additional application (and 75% do).

Rejected students can still be admitted to the program through quota 2, if they applied through quota 2. Analogous to quota 1 admissions, quota 2 seats with excess demand will maintain a program- and year-specific score cutoff and students whose score falls below the cutoff will not receive an offer of admission via quota 2. Some medicine programs also maintain a quota 2 stand-by list.

A student will only be admitted to at most one (pseudo) program. The student is only admitted to her most preferred program, among programs where she would be admitted, based on her extended preference ranking. In the empirical analysis, we hence distinguish between being "above the bar", meaning being above the GPA or the quota 2 score cutoff, and receiving an admissions offer. The student can then decide to accept (enroll) or reject the admissions offer, maintaining the option to enroll in programs with open enrollment only (without a binding GPA threshold) or re-apply to programs through the centralized application system in the future.

2.3 Dropout Rates in Medical School Programs

We focus our analysis on medical school programs in Denmark. There are four medicine programs: Copenhagen, Odense, Aarhus and Aalborg (with Aalborg opening in 2010). Despite being very selective in the admission process and drawing from the highest caliber high school graduates, Danish medical schools have had high program dropout rates, which continue to be at the forefront of active debate around changing admission standards. In fact, the dropout rate at Danish medical schools is among the highest of internationally reported

dropout rates. Mørcke et al. (2012) report a dropout rate of 20 percent at Aarhus University, which are concentrated in the first years of study. Among dropouts at Aarhus medical school, 63 percent leave in the first and 20 percent leave in the second year. In contrast, overall dropout rates from medical schools in other countries range between 2 and 3 percent in the UK and the US (Arulampalam et al., 2007; Stetto et al., 2004) or 12-20 percent in Australia and the Netherlands (Ward et al., 2004; Urlings-Strop et al., 2009; Cohen-Schotanus et al., 2006).[5]

While the causes of dropouts from medical school programs are not fully understood, evidence from Denmark and other countries suggests that individuals with lower entry qualifications have higher risks of dropping out (Yates and James, 2006; O'Neill et al., 2011b; Mørcke et al., 2012). Consistent with this, a sizeable fraction of dropouts struggle academically as indicated by failed exams in the early study years (Hojat et al., 1996; Yates, 2012; Maher et al., 2013).[6] In Denmark, the course curriculum is broadly standardized across medical school programs through a national accreditation agency ensuring that the content of the program course and faculty meet a certain standard. Likewise, there are standards for having exams co-graded by external teachers (e.g. from other medical programs, or university hospitals), again to ensure the quality of graduates. This suggests again that a student's academic fit and preparedness, that could potentially be elicited prior to admissions, is an important predictor of program completion.

In academic literature and the popular press, dropouts from medical school are perceived as a lose-lose-lose situation. Students who drop out lose time and self-confidence (Duffy et al., 2011; Liu et al., 2015), the medical school misses revenue, and to society a high dropout rate means wasted resources invested in the student and ultimately fewer medical doctors than was planned for and needed.[7] Consistent with this, we present direct evidence in Section 5 that programs consider the risk of dropout in their admission decisions. Motivated by these considerations, we focus on program dropouts as our primary outcome measure.

[5]Strayhorn (1999) report a dropout rate of 6 percent among disadvantaged students in the medical school program at the University of North Carolina Chapel Hill. While dropout rates tend to be higher in countries where students have direct entry from high school to medical school (Norman et al., 2012), we note that Australia, the Netherlands and Denmark all have direct entry from high school to medical school. That said, the dropout rates for medicine in Denmark are in the lower end for a Danish tertiary education program, suggesting that country specific factors including subsidized eduction and generous unemployment benefits contribute to high dropout rates overall.

[6]For example, in a retrospective cohort analysis at Aarhus' medical school program, Mørcke et al. (2012) report that 35 of the 80 dropouts in the first semester failed their first year exams and another 45 did not take the exams, suggesting that only out of 80 dropouts left in 'good academic standing.

[7]Universities in Denmark are funded by the government by means of a small base grant supplemented by a taximeter scheme. The taximeter funding accounts for 80% of total funding and is based on successfully completed study activity. Every year, all passed exams are counted together and converted into successful study years. Each exam contributes to the total study years according to it's pre-assigned cumulative study time. The total study years are then multiplied by a full-time equivalent taximeter rate `shorturl.at/uMSZ6`.

2.4 Odense's Admission Reform in 2002

Motivated by the high program dropout rates despite a strong applicant pool, the Faculty of Health Sciences at the University of Southern Denmark in Odense changed their admission process effective in 2002. A main goal of the reform was to identify students who are more likely to complete the program. Odense adopted two important changes. First, Odense filed an exemption from the Higher Education Act passed in 1999, which required medical school programs to increase their quota 1 share to 75 percent. This exemption allowed Odense to lower their quota 1 share to 50 percent in 2002. The quota 2 exemption from the higher education act was only discontinued in 2008 but put in place again from 2009 onward.

Second, Odense increased their screening efforts for quota 2 candidates, which are detailed in O'Neill et al. (2011a). In brief, Odense started to require a written motivational essay to assess the applicant's written communication skills, knowledge of the chosen program and profession, reflections on past experiences, reflections on choice of study, and future employment plans. The essay was rated by one staff member and given a score of 0-100 on a global rating scale. In addition, applicants were required to answer specific questions developed according to a national coordinated application system, that is used for applications to all higher education programs in Denmark. Answers were again rated by one staff member on a 0-100 global rating scale based on relevance and quantity of previous work experience; past educational qualifications; foreign exchange experiences, and organizational or voluntary work. Students who scored well on these assignments were invited for an admission test and an interview. The 15-minute admission test was a general knowledge test, covering many sub-domains, such as biology, physics, arts, news, music, health, politics, with 60 multiple-choice questions. The admission interview was a semi-structured interview designed to assess the applicant's subject interest; expectations; maturity for age; social skills; stress tolerance; empathy, and general interview behavior. The test and interview performance were again scored on a 0-100 global rating scale. The final admission test score was a weighted composite of scores for qualifications, general knowledge and the admission interview.

3 Theory

We now set up our theoretical model.

Agents: There are 2 programs, $j \in \{1, 2\}$, and a continuum of students of measure 1. Program j has $m_j^k \in [0, 1]$ quota-k seats, for $k = 1, 2$. Each student i in the set of students

$\mathcal{I}$ is characterized by characteristics

$$(x, u_1, u_2, \omega_1, \omega_2, s_1, s_2, c_{\{1\}}, c_{\{2\}}, c_{\{1,2\}})$$

distributed according to $Pr(x, u, \omega, s, c) = Q(x)F(u, \omega, s, c|x)$ on $X \times \mathbb{R}^2 \times \Omega^2 \times \mathbb{R}^2 \times \mathbb{R}^3_+$ where:

- X is a finite set with probability measure $Q(\cdot)$, representing "observables" such as the student's GPA and location.
- $u \in \mathbb{R}^2$ is the student's utility for each program, and is privately observed by the student.
- $\Omega \subseteq \mathbb{R}$ is the space of student "types" which enter colleges' payoffs.
- $s_j \in \mathbb{R}$ is a signal of ω_j that is privately observed by program j.
- $c \in \mathbb{R}^3_+$ are non-negative quota-2 application costs. To submit quota-2 apps to set A, a student pays c_A. (The cost of no quota 2 apps is assumed to be zero).
- $F(u, \omega, s, c|x)$ has a continuous positive density, $f(u, \omega, s, c|x)$.

Information is as follows: Each student's X is commonly observed by the student and both programs. Each student privately observes her own preferences (u_1, u_2) and quota-2 application costs $(c_{\{1\}}, c_{\{2\}}, c_{\{1,2\}})$. No player observes the value of ω of any student. Each program j privately observes s_j of each student who submits a quota-2 application to j. Finally, the model primitives $F(\cdot|x)$, $Q(\cdot)$, and capacities m are commonly known by all agents.

The game has the following timing. First, each student $i \in \mathcal{I}$ simultaneously observes her own (X, u, c), then chooses a rank-order list (ROL),

$$\ell_i \in \{(), (1), (2), (1,2), (2,1)\} \coloneqq \mathcal{L},$$

and a set of quota-2 applications $A_{ij} \in \{0, 1\}$. We say $\ell_i : j \succ k$ if ℓ_i ranks $j \in \{0, 1, 2\}$ ahead of $k \in \{0, 1, 2\}$.[8] Students cannot submit quota-2 applications to programs not on their rank-order list. That is, if j is not an element of ℓ_i then we must have $A_{ij} = 0$.

Second, programs simultaneously form rank-order lists for quota-2 admissions. Program j privately observes its applicants' characteristics and signals $\{(X_i, s_{ij}) : A_{ij} = 1\}$ and chooses

[8] Let 0 denote the outside-option program. A program is ranked ahead of the outside option if and only if it is included in ℓ_i.

a measurable *ranking function*

$$r_j : X \times [0,1] \to [0,1] \cup \{\emptyset\},$$

satisfying, for some $\tilde{r}_j$, $Pr(1 > r_j > \rho) = 1 - \rho$ for all $\rho > \tilde{r}_j$, and $Pr(r_j = \emptyset) = \tilde{r}_j$. The symbol $\emptyset$ denotes declaring a student unacceptable. If a student of type (X_i, s_{ij}) is not declared unacceptable then $r_j(X_i, s_{ij})$ denotes her percentile rank on j's list.

Third, students match to programs via the following process:

1. Each program is split into two pseudoprograms by quota, e.g. program j is split into $j^{(1)}$ with capacity m_j^1 and $j^{(2)}$ with capacity m_j^2.

2. Each quota-1 pseudoprogram ranks students according to an exogenously-given function of X. In practice, GPA is an element of X, and quota-1 pseudoprograms rank purely by GPA.

3. Each quota-2 pseudoprogram $j^{(2)}$ ranks students who applied quota-2 according to r_j. Students for whom $r_j = \emptyset$ are omitted (declared unacceptable).

4. Students' rank-order lists ℓ_i determine their ranking over quota-1 pseudoprograms. If a student submitted a quota-2 application, $A_{ij} = 1$, then the quota-2 pseudoprogram $j^{(2)}$ is inserted into i's rank order list just after $j^{(1)}$.

5. A student-proposing DA algorithm produces a matching. In iteration $t \geq 1$, each student points to her most-preferred pseudoprogram that has not yet rejected her; pseudoprograms reject unacceptable applicants; if the measure of applicants exceeds capacity, a pseudoprogram keeps its m_j^k highest-ranked applicants and rejects the rest; iterate to convergence.

Once the procedure terminates, students learn their placements.

Allocations and Payoffs: Student i receives

$$u_{ij} - c_{i,\{j:A_{ij}=1\}}$$

if she submits quota-2 apps A_i attends program j, and $-c_{i,\{j:A_{ij}=1\}}$ if unmatched. Students maximize expected utility by choice of quota-1 and quota-2 applications.

Before we state programs' payoffs, it is useful to define the following objects. Fix student strategies $(\ell, a) = (\ell_i, a_i)_{i \in \mathcal{I}}$ with $(\ell_i, a_i) \in \mathcal{L} \times \{0,1\}^2$ and program strategies $r = (r_j^q)_{j \in \{1,2\}, q \in \{1,2\}}$, where $r_j^1(s_j, x) \equiv r_j^1(x)$ is the exogenously given ranking of x's used in

quota-1 admissions, and $r_j^2(s_j, x) \equiv r_j(s_j, x)$ is the quota-2 ranking submitted by program j, which the quota-2 pseudoprogram inherits. Let the vector

$$\underline{r}^{(t)} = \{\underline{r}_{j,q}^{(t)}\}_{j\in\{1,2\},q\in\{1,2\}} \in [0,1]^4$$

denote the minimum score among students provisionally held by each pseudoprogram in iteration t, and let[9]

$$\underline{r} = \lim_{t\to\infty} \underline{r}^{(t)}$$

denote the minimum score among students matched to each pseudoprogram (equivalently: the "cutoff" percentile rank at each pseudoprogram) in the final allocation. Let

$$D_j^q(x, \underline{r}; \ell, a, r) \subset \mathcal{I}$$

denote the *the quota-q demand of school j of students of type x*, which is defined as the set of students of observable type x who are available to pseudoprogam (j, q) under the given strategies when the cutoffs of *pseudoprograms other than* (j, q) are given by the appropriate elements of $\underline{r}$. That, is, a student belongs to $D_j^q(x, \underline{r}; \ell, a, r)$ if and only if, given the student's application and the competing pseudoprograms' rankings and cutoffs, she will match to (j, q) whenever program (j, q) ranks her sufficiently highly. This set consists of students who have applied to (j, q) under the given strategies, and either prefer (j, q) to all alternatives to which they have applied, or do not qualify for admission to alternative programs that they ranked ahead of (j, q).[10] Where the meaning is clear, we may omit (ℓ, a, r) and write $D_j^q(x, \underline{r})$ for brevity.

We now state programs' payoffs. Pseudoprogram (j, q) receives ω_j from each student it

[9] The following limit exists as $\underline{r}^{(t)}$ is increasing in t.

[10] Formally, the quota 1 and 2 demands of schools j are given by

$$\begin{aligned} D_j^2(x, \underline{r}; \ell, a, r) &= (X = x) \cap (\{a_j = 1\} \cap \{r_j^1(x) < \underline{r}_j^1\}) \cap \\ &\qquad \big(\{\ell_i : j \succ k\} \cup (\{a_k = 0\} \cap \{r_k^1(s_k, x) < \underline{r}_k^1\}) \cup (\{r_k^2(s_k, x) < \underline{r}_k\} \cap \{r_k^1(s_k, x) < \underline{r}_k)\}\big) \\ D_j^1(x, \underline{r}; \ell, a, r) &= (X = x) \cap \{\ell_i : j \succ 0\} \cap (\{\ell_i : j \succ k\} \cup \\ &\qquad (\{a_k = 0\} \cap \{r_k^1(s_k, x) < \underline{r}_k^1)\}) \cup (\{r_k^2(s_k, x) < \underline{r}_k\} \cap \{r_k^1(s_k, x) < \underline{r}_k\}). \end{aligned}$$

In the event that $\ell_i = \ell_i^*$ is truthful, this expression can be written as

$$\begin{aligned} D_j^2(x, \underline{r}; \ell, a, r) &= (X = x) \cap (\{a_j = 1\} \cap \{r_j^1(x) < \underline{r}_j^1\}) \cap \\ &\qquad \big(\{u_j > u_k\} \cup (\{a_k = 0\} \cap \{r_k^1(s_k, x) < \underline{r}_k^1\}) \cup (\{r_k^2(s_k, x) < \underline{r}_k\} \cap \{r_k^1(s_k, x) < \underline{r}_k)\}\big) \\ D_j^1(x, \underline{r}; \ell, a, r) &= (X = x) \cap \{u_j > 0\} \cap (\{u_j > u_k\} \cup (\{a_k = 0\} \cap \{r_k^1(s_k, x) < \underline{r}_k^1)\}) \\ &\qquad \cup (\{r_k^2(s_k, x) < \underline{r}_k\} \cap \{r_k^1(s_k, x) < \underline{r}_k\}). \end{aligned}$$

is matched to. A student i of type x is matched to pseudoprogram (j,q) if $i \in D_j^q(x)$ and $r_j^q(s_{ij},x) > \underline{r}_j^q$. Hence, the pseudoprogram's payoff is

$$\Pi_{(j,q)}(r_j, r_k, a, \ell) = \int_{D_j^q(x)\cap\{r_j^q(s_j,x)\geq \underline{r}_j^q\}} \omega_j \; dF(u,\omega,s,c,x).$$

A program's payoff is the sum of the payoffs of the quota-1 and quota-2 pseudoprograms that comprise it.

Analysis: We first argue that students report their quota-1 applications truthfully. Because Quota-1 applications are free, a student-proposing DA algorithm is used, and pseudoprograms of the same program give the same utility, it is weakly dominant for students to report their quota-1 rank-order list ℓ truthfully. Let ℓ^* denote the truthful list.

The optimal Quota-2 decision depends on programs' strategies, and on students' beliefs about admissions chances. In this draft, we make the following behavioral assumption on programs' strategies.

Assumption 1 (Truthful Ranking) *Let students' strategies be given by (ℓ^*, a^*). Each program j ranks applicants according to their expected payoff conditional on matching to j, that is, $r_j(s_{ij},x) > r_j(s'_{ij},x')$ if and only if*

$$E(\omega_{ij}|s_{ij}, i \in D_j^2(x,\underline{r};\ell^*,a^*,r)) > E(\omega_{ij}|s'_{ij}, i \in D_j^2(x',\underline{r};\ell^*,a^*,r)).$$

This assumption says that programs are sophisticated about interdependent values, and any selection on application decisions induced by correlation between talents ω and utilities or application costs, but requires that programs be naive about additional strategic complications induced by the use of the deferred-acceptance procedure.[11] We believe this assumption captures programs' behavior well, but in future drafts we will also consider Nash Equilibrium.

Students form rational expectations about Quota-2 admissions chances in equilibrium. To close the model, we need an assumption about students' beliefs over Quota-1 admissions

[11] In general, in many-to-one stable matching mechanisms, programs may have incentives to engage in capacity reduction, or to declare some applicants unacceptable (Sönmez, 1997). In our setting, the government sets binding constraints on programs' capacities and quota-2 shares, such that programs would not wish to further reduce capacities. However, a program might wish to discriminate against students who are likely to set off "rejection chains". Intuitively, if a student, i, prefers program j but would attend k if he is rejected by j, then if program j rejects the student he may cause k to reject another student, i', in the course of the DA algorithm, whom j prefers to i'. Such rejection chains may occur only when i prefers j to k to 0, and hence programs may wish to set a "higher bar" for students who are likely to have these preferences. Empirical evidence presented in Appendix Section C.7 suggests that the potential for successful rejections chains is very limited in our setting. Our assumption abstracts from these incentives.

chances. We assume that students observe their own GPA as well as previous years' Quota-1 cutoffs, and form beliefs about the current year's cutoff when choosing a^*. In our empirical model we specify a model of adaptive expectations, which we describe in section 6.

We make two statistical assumptions which ensure that programs employ cutoff strategies, admitting students with signals s_j above an X-specific cutoff value.

Assumption 2 (Conditional Independence) *For all x, the distribution of program signals and other variables satisfies the following conditional-independence condition:*

$$f(u, \omega, s, c|x) = f_{u,\omega,c}(u, \omega, c|x) f_{s_1|\omega,x}(s_1|\omega, x) f_{s_2|\omega,x}(s_2|\omega, x).$$

This assumption, which we maintain in our empirical model, requires that programs' mistakes in evaluating candidates are independent. They do not, for example, misread the application materials in the same way. Programs' signals may be correlated because the true talents, of which they are signals, may be correlated.

Our next assumption requires that higher signals are better in a strong sense.

Assumption 3 (MLRP) *For all x, for $j = 1, 2$, the density $f(s_j|\omega, x)$ satisfies the strict monotone likelihood ratio property in (s_j, ω_j). That is, $f(s'_j|\omega_j, x)/f(s_j|\omega_j, x)$ is monotone increasing in ω_j for $s'_j > s_j$. Moreover, for $s'_j > s_j$ we have*

$$\lim_{\omega_j \to \infty} \frac{f(s'_j|\omega_j, x)}{f(s_j|\omega_j, x)} = \infty$$

and

$$\lim_{\omega_j \to -\infty} \frac{f(s'_j|\omega_j, x)}{f(s_j|\omega_j, x)} = 0.$$

Under these assumptions, we show that $E(\omega_j|s_j, i \in D_j^2(x, \underline{r}; \ell^*, a^*, r))$ is monotone in s_j and hence, under the equilibrium student strategies and "truthful" program rankings, there are program-specific cutoff functions $\underline{s}_j(x)$, varying with observables x, such that the quota-2 pseudoprogram $(j, 2)$ is available to students of type x for whom $s_j > \underline{s}_j(x)$. We state this result in the following Proposition:

Proposition 1 *Under assumptions 1, 2, and 3, program j's Quota-2 ranking function $r_j^2(s_j, x)$ is increasing in s_j for all x, for each j. Moreover, there exist program-specific cutoff functions $\underline{s}_j(x)$ such that $r_j^2(\underline{s}_j(x), x) = \underline{r}_j^2$. Students of type x match to pseudoprogram $(j, 2)$ if and only if they belong to $D_j^2(x)$ and have $s_j \geq \underline{s}_j(x)$.*

The proof is given in the appendix. In our empirical analysis, this result allows us to interpret programs' rankings and observed admissions outcomes, as rankings are monotone in signals conditional on X.

4 Data

The dataset in this paper combines several administrative micro data sets providing detailed information on medical school applications, admissions, enrollment, and outcomes.

4.1 Sample Construction

Our primary data source is college application data from the Danish Central Admissions Secretariat (CAS), which provides us with information on submitted preference rankings and admission decisions for application cohorts 1994-2013. We focus on applicants who indicate either at least one medical school program or at least one program considered a close substitute to the medical programs in their submitted preference ranking. Close substitute programs contains the three most common university level programs for applicants applying to the medical programs in Aarhus, Odense and/or Copenhagen and comprises programs in dentistry, psychology and clinical biomechanics (as well as the medical school in Aalborg that did not open until 2010 with a small student uptake).[12] Our data allow us to distinguish between quota 1 and quota 2 admissions. We focus on admissions through regular quotas 10 (subset of quota 1) and 20 (subset of quota 2), which comprise more than 90% of all medical school admissions. These quotas exclude applicants from non-EU countries who are offered their own (albeit small in number) program seats and hence follow different admission standards.[13] In our main analysis, we focus on admissions to Odense and Aarhus, which we argue below is the closest substitute to Odense and thereby most affected by Odense's information experiment.

We merge the college application data with several complementary data sources. First, we merge the application data with programs' quota 2 applicant ranking lists. These lists provide information on how programs rank their quota 2 applicants. Second, we merge the combined data with student enrollment data, which contain the start and end dates of higher education by field of study and institution, as well as program exit codes indicating dropouts, transfers, and completion. Finally, we merge the combined data with population registry data, which provides us with student demographics, admissions, and outcomes. Specifically, we add applicants' high school GPA, nationality, and region of residence.[14]

[12] This 'market' definition allows us to zoom into the relevant student population. We note that 98.9% of university applicants do not use up all their 8 preferences, suggesting that students interested in medicine can list a medical school program without compromising their admission chances into other programs, and hence make it into our sample.

[13] Applicants in groups 10 and 20 can further opt to apply for standby seats, which are assigned in a separate group after regular quota 1 and 2 admission.

[14] We do not observe high school GPA for degrees obtained outside of Denmark. However, we are able to impute their GPA based on the programs' quota 1 ranking lists.

4.2 Descriptives

Our sample consists of 35,759 medical schools applicants over the years 1994-2013. Copenhagen is the most popular program, which receives 30,356 applications ($\approx$ 1,500 per year), see Table 1, followed by Aarhus and Odense. Aalborg opened a small medicine program with less than 100 seats in 2010. 68% of applicants to Copenhagen list Copenhagen first in their quota 1 rank-ordered list. For Aarhus and Odense this share drops to 44.% and 29.2%. The preference ranking changes qualitatively when conditioning on the student's former residence. In Figure 1a we display the share of applicants that list Aarhus first, or that list Copenhagen (or much less frequently Aalborg[15]) first and Aarhus second (A and A2), the share that list Odense first, or Copenhagen first and Odense second (O and O2), and the share that neither list Aarhus nor Odense first or second (X), by region of residence. Among applicants from Odense, only about 30% of students applying to any medical school program list Copenhagen or Aalborg first, which corresponds to the sum of regions O2, A2, and X. Instead, almost 60% rank Odense first. Similarly, over 70% of students from Aarhus list Aarhus first. This points to an important "home bias" in student preferences.

Most students interested in the medical programs in Aarhus or Odense only apply through quota 1. Odense has the lowest share of quota 2 applicants. Only 15.4% of quota 1 applicants also apply via quota 2, which is consistent with Odense's thorough screening procedure that is costly for applicants. Figure 1b summarizes key patterns for quota 2 applications. Here, we focus on students who apply to Aarhus or Odense through quota 1 and we distinguish applicants according to their relative preference for Aarhus or Odense and based on their expected quota 1 admission chances. Specifically, we consider students whose GPA is substantially higher (lower) than the GPA threshold in Aarhus and Odense in the past two years as likely to be admitted (rejected) in quota 1. For each group, we denote the share of applicants that submits a quota 2 application to Aarhus, Odense, both, or none denoted by "N".

Only a small share of students with high quota 1 admission probability (high Pr(Q1)) applies through quota 2 even at their preferred program. In contrast, students with low quota 1 admission chances use quota 2 more frequently. This suggests that applicants take into account their chances of admission through quota 1 when deciding to apply through quota 2. Nevertheless, a large share of students with low GPA also rely on quota 1 applications only, consistent with applicants being unconstrained in their priority lists. Finally, Figure 1b shows that quota 2 applications to Aarhus are much more frequent and even students who

[15]Categories A2, O2 and X include applicants that list Aalborg first in 2010–2013. Yet, this is a small share of the sample and the patterns are driven by applicants preferring the flagship program in Copenhagen, see Appendix figure.

Table 1: Summary Statistics: Medical School Applicants

	Copenhagen	Aarhus	Odense	Aalborg
Applicants	28,580	24,200	21,639	3,716
Share listing j as 1st Priority	0.676	0.445	0.292	0.164
Share submitting Quota 2 Application to j	0.62	0.34	0.154	0.57
Admitted	10,478	7,540	4,830	249
Admitted via Q1	8,694	5,921	3,007	223
GPA Cutoff Q1	9.852	9.621	9.519	10.36 †
Enrolled	7,866	6,391	4,071	205
1y Dropout Rate	0.05	0.055	0.051	0.102
3y Dropout Rate	0.121	0.132	0.122	0.166
1y Transfer Rate	0.003	0.004	0.006	.§
3y Transfer Rate	0.005	0.012	0.016	.§
10y Completion Rate	0.834	0.839	0.83	.‡
Sample Years	1994-2013	1994-2013	1994-2013	2010-2013

Note: This table presents summary statistics for our main sample. †*: GPA cutoffs have been increasing over the sample period due to an increase in applications, which explains Aalborg's higher average GPA. Copenhagen has a GPA cutoff of about 10.5, exceeding Aalborg's, when considering years 2010-2013 only, see Appendix Figure 16e.* §*: transfer rates for Aalborg cannot be reported due to insufficient case numbers.* ‡*: the 10y completion rate is omitted for Aalborg due to the short sample period of four years.*

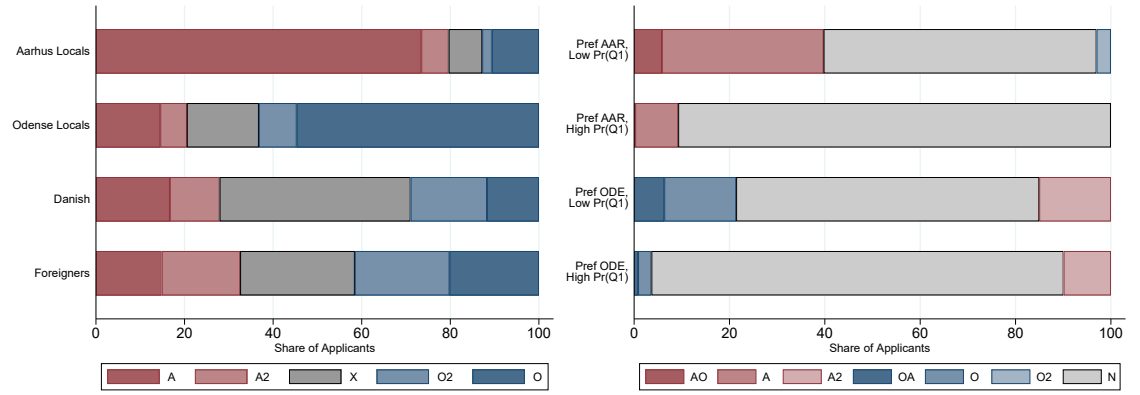
prefer Odense often only apply through quota 2 to Aarhus. Together, these patterns suggest substantial differences in quota 2 application costs and point to important substitution patterns between Odense and Aarhus students, which we return to below.

About 25% of applications to any medical school program are admitted, see Table 1. The largest program is Copenhagen (≈ 520 admissions per year) followed by Aarhus (≈ 375 admissions per year) and then Odense (≈240 admissions per year). The number of program admissions are quite stable over time, with a modest expansion across all existing programs in 2009, see Appendix Figure 16a for details. At the same time, the number of applicants per year that apply to at least one medical program in Denmark gradually increased from 2,200 in the late 1990s to 3,300 after 2010, see Appendix Figure 10. About 75% of admitted applicants are admitted via quota 1, a share that has increased in Aarhus and Copenhagen from less than 60% to 90% over the sample period due to two higher education reforms. In contrast, Odense filed an exemption to these reforms, allowing the program to maintain a quota 1 share of about 50% since 2002, see Appendix Figure 16b.

Copenhagen is the most competitive program in any year during our sample period despite being the largest, as evidenced by a higher GPA cutoff than Odense and Aarhus.[16] About 88% of admitted students enroll in the program.

[16]GPA cutoffs have been increasing over the sample period due to an increase an applications, which explains Aalborg's higher average GPA. Copenhagen has an a GPA cutoff of about 10.5, exceeding Aalborg's, when considering years 2010-2013 only, see Appendix Figure 16e.

Figure 1: Program Preferences and Admission Chances by Residence



(a) Preferences by Former Residence (b) Quota 2 Applications

Note: Figure 1a plots the composition of applicant preferences by area of residency, see Appendix Section A.1 for geographic details. Within each region, we display the share of applicants by five preference types. "A" denotes that an applicant's first priority among medical programs is Aarhus, and "O" denotes top priority for Odense. "A2" and "O2" denote preference rankings where an applicant lists a flagship program of either Copenhagen or Aalborg first, and Aarhus (A2) or Odense (O2) second. "X" denotes cases where applicants do not list Aarhus or Odense as either first or second priority. Figure 1b plots the composition of quota 1 and quota 2 applications among students applying to Odense and/or Aarhus. We group applicants by their relative preference over the two programs (prefer Odense or prefer Aarhus) and focus on applicants with a GPA at least 0.3 points above the maximum (high Pro(Q1)) (below the minimum (Low Pr(Q1))) of the GPA thresholds in Aarhus and Odense over the previous two years. Here, "A" denotes a quota 2 application to first-choice program Aarhus, and "O" analogously denotes a quota 2 application to Odense. "AO" and "OA" denote a quota 2 application to both programs in the order of the student's relative preferences. "A2" and "O2" denote quota 2 applications only to Aarhus or Odense in case these programs are a student's less preferred choice. "N" refers to student who only submit a quota 1 application.

Consistent with the literature, we find that a substantial fraction of admitted students drops out over the course of the program. About 5% of enrolled students drop out in the first year of study and 12-13% drop out in the first three years of the program. Only 83% of students complete the program, which also suggests that most of the dropouts (12.5%/(1-83%=74%) dropout out within the first three years of study. We therefore focus on the three-year dropout rate as our main outcome measure, which we can construct for all applicants in our sample period as we observe dropout outcomes until 2015. Our dropout measure includes program transfers to other medical programs to reflect the objectives of each school: from a program's perspective transfers imply a loss in private surplus. We note, however, that transfers are relatively rare in the first three years of the program. Only 0.3% (0.5%) of enrolled students transfer in the first year (first 3 years) to another medical program. We further provide robustness using the field-specific dropout rate (netting out transfers) to capture potential medical doctors lost to the profession.

4.3 Aarhus and Odense

We focus our main analysis on admissions to Odense, where the information experiment took place, and Aarhus which is the closest substitute among the medical school programs throughout our sample period. Aalborg only opened their medical school program in 2010

and hence did not compete with Odense throughout most of our sample period. Copenhagen's program is the country's flagship program and vertically differentiated from Odense and Aarhus as evidenced by the a higher GPA cutoff and the revealed popularity in student applications.

We assess the substitution patterns between medical school programs more rigorously in Appendix Table 9. We document that most students applying to Odense also apply to Aarhus (69%) and Copenhagen (66%). However, due to high popularity of Copenhagen's medical school program and their competitive admission standards, only 0.7% of rejected students at Odense are admitted to Copenhagen, reducing the potential importance of a winner's curse. This share increases more than threefold to 2.7% when considering admissions to Aarhus. Similarly, about 4.3% of admitted students to Aarhus were rejected at Odense, a share that drops to 0.8% when considering admissions at Copenhagen. In addition, one-third of applicants to Odense list Aarhus medicine as their next priority, and 36 percent of Aarhus applicants list Odense next. As such, Aarhus and Odense are revealed as closest substitutes among applicants, with these shares being substantially larger than the fraction of applicants who list Copenhagen next (20 and 21 percent among ODE and AAR applicants, respectively).

These statistics indicate that potential spillover effects of Odense information experiment should be most pronounced at Aarhus, motivating our focus on these two programs in the remainder of the analysis.

5 Interdependent Values and Program Admissions

In this section, we explore the role of interdependent values and how they affect programs' admission decisions. We start with evidence on programs' admission preferences for program persistence and document that programs hold some but not complete information about applicants' dropout outcomes. We present evidence consistent with interdependent values and explore whether programs' admission decisions are consistent with the presence of interdependent values. Our technical definition of interdependent values is that the expected talent may depend on program signals and student preferences:

$$E[\omega_j | s_j, s_{-j}, u_j, X] \ . \tag{1}$$

Below, we distinguish between interdependent program values, that capture the relationship between ω_j and s_{-j}, conditional on s_j, X, and student selection, which captures the relationship between ω_j and u_j, conditional on s_j, X. We present evidence on interdependent program values in subsection 5.4 and evidence on student selection in subsection 5.5.

5.1 Programs' Admission Preferences

To investigate programs' objectives behind their admission decisions, we start by comparing student characteristics between quota 1 admissions and discretionary admissions through quota 2 using a regression discontinuity design (RDD). The RDD analysis excludes students admitted to higher ranked programs (by the student) and hence focuses on marginal students, students who belong to D_j^q using the notation from Section 3, who receive an admissions offer if they are above the bar.

Recall that quota 1 admissions purely depend on GPA as evidenced by Figure 2a, which plots the fraction of admitted applicants to Odense, Aarhus, or Copenhagen by quota on the vertical axis. On the horizontal axis, we measure the difference between the applicant's GPA and the program's GPA cutoff in grade-points. As the GPA passes the GPA threshold, the probability of being admitted via quota 1 quickly shoots to 100 percent.[17] Below the GPA threshold, we consider Quota 2 admission chances among applicants available to each program, D_j^q. While the pooled Figure 2a shows evidence for an increase in quota 2 admission chances in applicants' GPA, additional analysis by program reveals that this patterns is entirely driven by Aarhus. The average admission chance at Aarhus increases from 20% for applicants with 1 GPA point below the threshold to about 50% among students whose GPA is close to the cutoff, see Appendix Figure 17. In contrast, Quota 2 admission chances at both Odense and Copenhagen medical schools do not depend on GPA. In addition, we find level differences in admission chances, from 20% in Copenhagen to 80% at Odense, consistent with level differences in the share of Quota 2 applications to each program.

To test whether the additional and admission-relevant information collected through the quota 2 review process is correlated with student persistence, we test for differences in dropout rates among admitted students at the GPA cutoff. Figure 2b presents a sharp difference in the three year-dropout rate between quota 2 and quota 1 admits at the GPA cutoff.

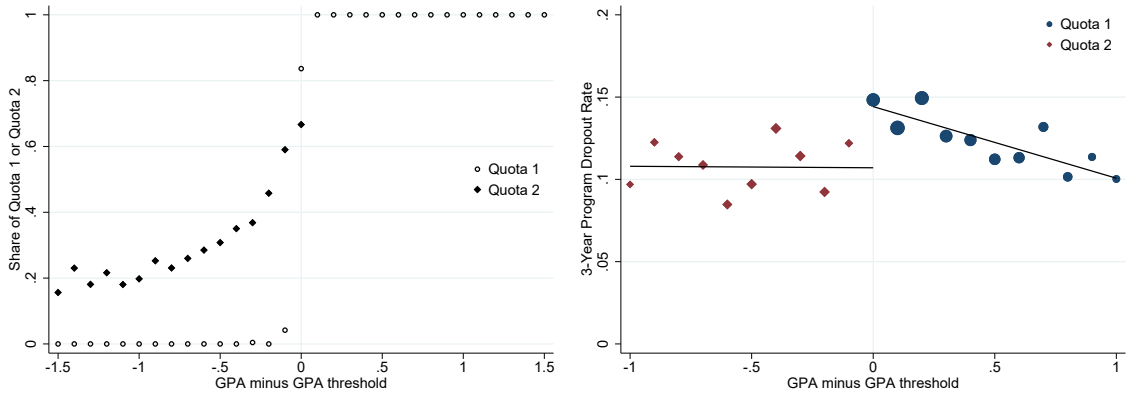
To quantify this drop more formally, we estimate a simple stacked RD model, that controls for differential linear trends to the left and right of the GPA cutoff. Specifically, we estimate the following regression model:

$$\begin{aligned} Y_{ijt} &= \gamma_0 + \gamma_{gpa_{q1}} \cdot gpa_i \cdot \mathbb{1}\{GPA \geq cutoff\} + \gamma_{gpa_{q2}} \cdot gpa_i \cdot \mathbb{1}\{GPA < cutoff\} \\ &+ \gamma_s \cdot \mathbb{1}\{GPA < cutoff\} + \gamma_{jt} + \epsilon_{ijt}, \end{aligned} \tag{2}$$

where gpa_i denotes the difference between the student's GPA and the GPA cutoff, denoted

[17] Measurement error in the GPA in select sampling years explains why the quota 1 admission chance slightly exceeds 0% below the GPA cutoff.

Figure 2: Admissions and Dropouts by Quota



(a) Admissions and Distance to GPA Cutoff (b) Dropouts by Distance to GPA Cutoff

Note: Figure 2a plots the pooled fraction of admitted applicants to Odense, Aarhus, and Copenhagen by quota on the vertical axis. On the horizontal axis, we measure the difference between the applicant's GPA and each program's GPA cutoff in grade-points. Figure 2b maintains the same horizontal axis but plots the 3-year dropout rate on the vertical axis for students across all programs. This figure omits students admitted via quota 1 (quota 2) whose GPA is below (above) the GPA cutoff. The lines denote the best linear fit of dropouts on GPA among quota 1 and quota 2 enrollees, weighted by the number of observations in each bin.

as 'cutoff', and γ_{jt} denotes program-by-year fixed effects. The parameter of interest is the effect of crossing the GPA threshold from the right to left, γ_s, which we refer to as the effect of quota 2 through signaling and screening. Table 2 presents this parameter estimate for different dropout outcome measures in the first row. We find that at the GPA cutoff margin, students admitted via quota 2 have a statistically significant 5.2 p.p. lower three-year dropout rate than students admitted via quota 1, see column 1. This difference falls slightly to 4.5 p.p when excluding transfers into other medical school programs from our dropout measure, see column 2. The result are qualitatively similar when considering alternative persistence measures such as the one-year dropout rate, completion rate, or the time to complete, see Appendix Table 10.

While the effect of quota 2 screening on dropout is similar between Aarhus, column 3, and Odense, column 4, we note that average dropout rates among students admitted via quota 2 differ substantially across the two programs. The estimates suggest a steep increase in the dropout rate among lower-GPA students admitted via quota 2 at Aarhus, whereas dropout rates by GPA among quota 2 students at Odense are constant. We find a smaller effect of Quota 2 screening at the GPA threshold in Copenhagen, which could be related to a larger share of Quota 2 applicants and hence weaker self-selection than in other programs. Mirroring the regression evidence, Appendix Figure 17 shows these patterns and the discrete difference in dropout rates at the GPA threshold for each program separately.

One potential contributor to the difference in dropout rates between quota 1 and quota 2 admissions could be differences in student motivation, if quota 2 applicants are on average

Table 2: Programs' Information Quality and Student Dropout Rates

	(1) 3Y Dropout	(2) 3Y Med Dropout	(3) 3Y Dropout (AAR)	(4) 3Y Dropout (ODE)	(5) 3Y Dropout (CPH)
γ_s	-0.052***	-0.045***	-0.071***	-0.062***	-0.036
	(0.013)	(0.013)	(0.021)	(0.023)	(0.026)
$\gamma_{gpa_{q1}}$	-0.003***	-0.003***	-0.007***	-0.003	-0.001
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
$\gamma_{gpa_{q2}}$	-0.002	-0.001	-0.009**	-0.001	0.001
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)
Constant	0.266***	0.135***	0.129***	0.141***	0.124***
	(0.028)	(0.027)	(0.018)	(0.024)	(0.016)
Observations	15,554	15,554	5,474	3,241	6,839

*Note: This table presents estimates from regression model (2). Column 1 considers the three-year dropout rate at any enrolled program among admitted students to Aarhus or Odense. Column 2 exclude transfers into other medical programs in measuring dropouts. Columns 1 and 2 pool enrolled students at both institutions, whereas Column 3 and 4 analyzes only students enrolled in Aarhus or Odense, respectively. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

more motivated and willing to go through the application process. To control for this possibility, we revisit the analysis among quota 2 applicants. Specifically, we exclude students that were admitted via quota 1 but did not apply via quota 2. We now find qualitatively similar effects that are about 50% smaller in magnitude. Nevertheless, the effects remain statistically significant for two out of four persistence measures despite the smaller sample size, see Appendix Table 11 for details. This suggests that differences in student selection may contribute to the observed difference but cannot explain it in full.

5.1.1 Evidence from Program Rankings

In addition to the discontinuity at the GPA threshold, we also explore the correlation between the program's quota 2 ranking and dropouts. To this end, we conduct an RD analysis of dropouts analogous to equation (2), but using the percentile rank of students admitted via Quota 1 and Quota 2 in each cohort, respectively, as the running variable. Specifically, in Figure **??** we rank students admitted through Quota 2 from -1 for the highest-ranked student to 0 for the lowest, while Quota 1 admissions are ranked from 0 for the student with lowest GPA to 1 for the highest. Note that the order is from best to worst among Quota 2 students, but from worst to best among Quota 1 students, such that the marginal students from each Quota are comparable at 0.

Analyzing dropout rates for the pooled sample of students at Copenhagen, Aarhus, and Odense, Figure **??** shows that the highest-ranked students admitted through Quota 2 have substantially lower average dropout rates than the students with highest GPA admitted through Quota 1. The clear positive slope among Quota 2 students suggests that programs extract dropout-relevant information during the screening process and use this information in forming their rankings. Finally, Figure **??** suggests that the marginal admissions through

Quota 1 and Quota 2 (around the 0 threshold in the graph) have similar dropout rates, consistent with efficient allocation of seats across the two quotas.

However, analyzing outcomes separately by program reveals substantial differences: While Copenhagen and Odense extract and act on dropout-relevant information in their Quota 2 rankings, the ranking at Aarhus is not predictive of dropouts among Quota 2 students. In addition, marginal Quota 2 students at Copenhagen are somewhat worse than marginal Quota 1 students, whereas the opposite is true at Odense. Running a regression analogous to equation (2) using the percentile rank from -1 to 1 as in Figure **??** instead of GPA as the running variable, we find a 3.7 p.p. lower dropout rate among marginal Quota 2 students at Odense compared to marginal Quota 1 students, significant at 10% level, see Appendix Table 12. This suggests than increasing the share of Quota 2 seats at Odense could improve average student outcomes there.

Focusing on Quota 2 applicants, we further investigate whether program rankings predict persistence in other programs as well. Appendix Tables 13, 14, and 15 show strong evidence that higher ranked students by all three medical programs, Aarhus, Odense, and Copenhagen, have lower dropout rates if they end up studying at other non-medical programs. Copenhagen's ranking is also a strong predictor of success in other medical programs, whereas the relationship between program rankings and outcomes in other medical programs is underpowered for Aarhus and Odense because fewer applicants rejected there are admitted to another medical program.

Taken together, this evidence suggests that programs care about persistence in their (discretionary) admission decisions and have at least some information about persistence. This is consistent with the incentives provided by government funding, which reimburses programs on the basis of enrolled students, see footnote 7 for details. There also seem to be clear differences in information quality extracted during the screening process across programs, consistent with the information experiment that we analyze next.

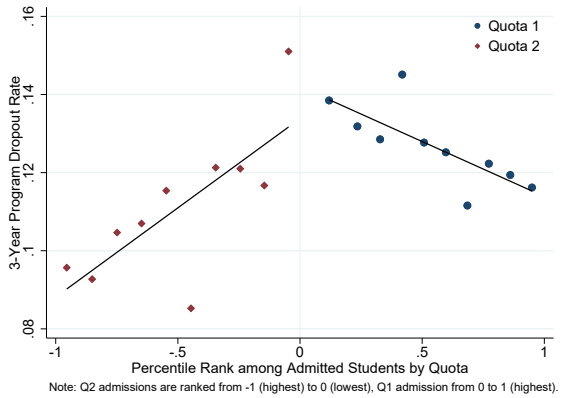
5.2 Interdependent Values and Odense's Information Experiment

While programs collect some information about student persistence, it seems plausible that programs remain uncertain about students' talents. In particular, a rival program and or the student herself may possess information about the student's completion rate that would, if known by the program, affect the program's assessment of student talent.

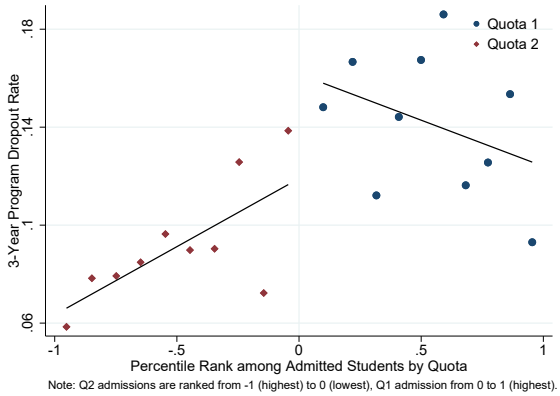
To investigate these claims, we turn to Odense's information experiment. We start by exploring the effects of the experiment on Odense's own dropout rate. Figure 4a presents the 3-year dropout rates among enrolled students by program and the start year (cohort).[18]

[18] We first residualize 3-year dropout rates controlling for GPA fixed effects and the share of Q2 admissions

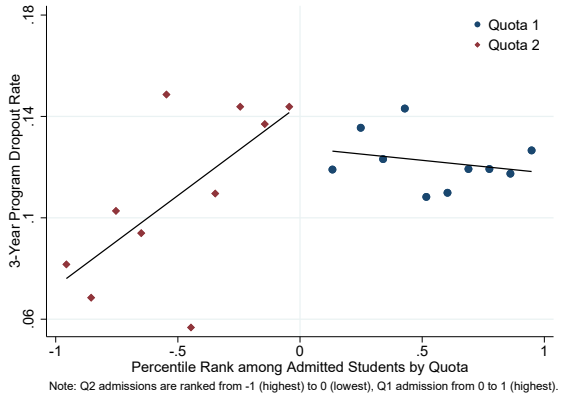
Figure 3: Admissions and Dropouts by Quota



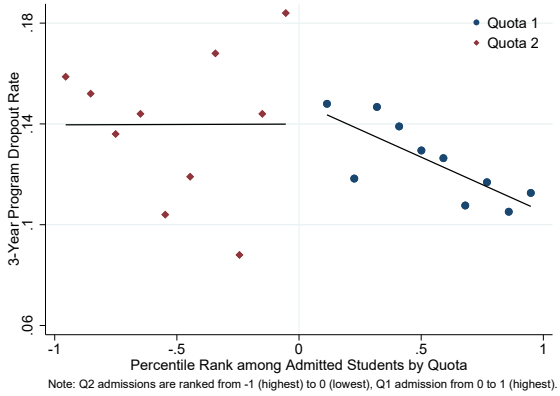
(a) Dropouts by Rank within Quota: Pooled



(b) Dropouts by Rank within Quota: Odense



(c) Dropouts by Rank within Quota: Copenhagen

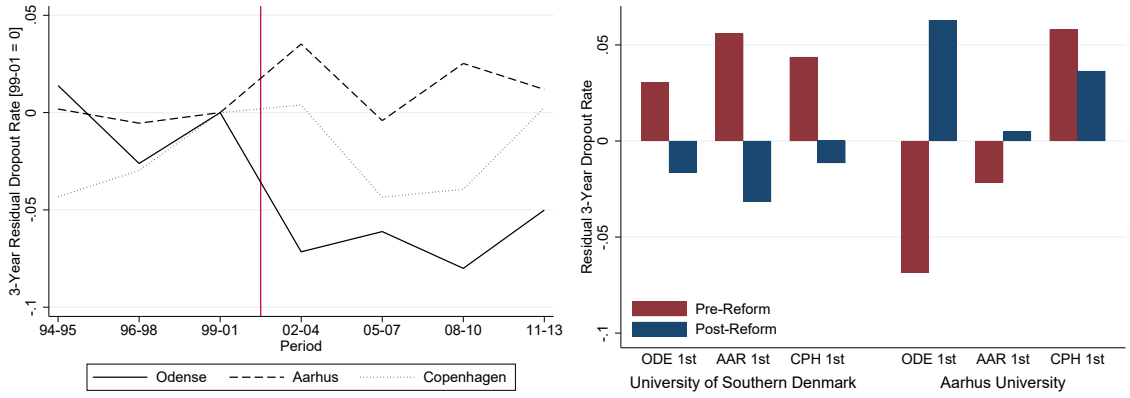


(d) Dropouts by Rank within Quota: Aarhus

Note: This figure plots the 3-year dropout rate on the vertical axis and ranks enrolled students on the x-axis according to their percentile rank in their admission quota. Quota 2 admissions are ranked from -1 for the highest-ranked student to 0 for the lowest, while Quota 1 admissions are ranked from 0 for the student with lowest GPA admitted through Quota 1 to 1 for the highest. We split students into 10 equally sized bins (deciles) within each quota and lines denote the best linear fit. Figure 3a shows results for students pooled across all programs, while the other figures report results for each program separately. Each figure split students into 10 equally sized bins (deciles) within each quota. The lines denote the best linear fit among quota 1 and quota 2 enrollees, weighted by the number of observations in each bin.

We include Copenhagen in the analysis but focus on the effects at Odense and Aarhus as the closest substitute program. We pool 3 cohorts into one observation, normalize the period 1999-2001 before the reform, and plot average dropout rates over time. While dropout rates followed similar trends at Odense and Aarhus before 2002, Figure 4a shows that Odense's 3-year dropout rate falls by 5 percentage points among students admitted between 2002 and 2004, whereas dropout rates at Aarhus increased by 3 percentage points.

Figure 4: Dropout Rates in Odense and Aarhus and Odense's Admission Reform



(a) 3-Year Dropout by Program and Cohort (b) Persistence at Aarhus by Preference

Note: The vertical line in Figure 4a delineates the timing of Odense's admission reform.

To quantify the impact of the reform on Odense's dropout rate more formally, we compare dropout rates across medical programs before and after the reform using a difference-in-differences research design. Specifically, we estimate the following regression model:

$$Y_{ijt} = \gamma_j + X'_{ijt}\gamma_c + \gamma_P \cdot Post_t + \gamma_{DID} \cdot Post_t \cdot Odense_j + \epsilon_{jt}, \tag{3}$$

where *Post* takes value 1 for the post-reform cohorts 2002-2013, and *Odense* is an Odense fixed effect. The key parameter of interest is γ_{DID}, which denotes differential changes in persistence among students admitted to Odense in the post-reform years. Table 3 presents this parameter estimate for different persistence measures.

We find that students admitted to Odense after the reform have significantly lower dropout rates. The one-year dropout rate falls by 4.2 p.p. and the three-year dropout rate falls by 7.2 p.p., see columns 1 and 2. The effect sizes drop slightly when excluding program transfers. We see qualitatively similar results when considering the completion rate or the time to completion among cohorts first enrolling 1994-2009, see columns 5 and 6. We also find qualitatively similar results in alternative sample populations, such as excluding stand-by admissions or restricting the post-reform years, see Appendix Table 17.

in each program.

Table 3: Student Persistence at Odense and the Admission Reform

	(1) Prog 1y	(2) Prog 3y	(3) Med 1y	(4) Med 3y	(5) Completion	(6) Study Time
Post · Odense	-0.042***	-0.072***	-0.034***	-0.046***	0.038**	-118.284***
	(0.010)	(0.015)	(0.010)	(0.014)	(0.018)	(19.380)
Constant	0.058***	0.135***	0.053***	0.121***	0.832***	2,606.510***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(4.276)
Observations	18,114	18,114	18,114	18,114	13,403	11,198
R-squared	0.037	0.049	0.037	0.047	0.052	0.134

*Note: This table presents estimates from Equation 3. Columns 1 and 2 report results for program-specific dropout rates including transfers, while columns 3 and 4 exclude transfers. Column 5 analyzes completion rates for cohorts who first enroll in medical programs over 1994-2009. Conditional on completion among cohorts 1994-2009, column 6 measures average time until graduation. All specifications control for resident location by school fixed effects and year by GPA fixed effects. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 4: Aarhus' 3-Year Dropout Rates and the Admission Reform

	(1) All	(2) Ever Enrolled Med	(3) Ever Enrolled AAR	(4) Enrolled AAR
Prefer Odense × Post	0.123**	0.151**	0.157**	0.116*
	(0.058)	(0.063)	(0.063)	(0.066)
Prefer Odense	-0.040	-0.031	-0.031	-0.031
	(0.053)	(0.056)	(0.056)	(0.056)
Constant	0.126***	0.130***	0.129***	0.129***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	7,487	6,803	6,746	6,333
R-squared	0.075	0.082	0.084	0.089

*Note: This table presents estimates from Equation 4. Column 1 includes all students admitted to Aarhus and analyzes dropout in the first enrolled program. Column 2 restricts the sample to admitted students who ever enroll in a medical program, while column 3 further restricts this sample to those who ever enroll in Aarhus. Column 4 reports results for admitted students who immediately enroll in Aarhus medical school. All specifications control for resident location fixed effects and year by GPA fixed effects. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Together, the evidence from Figure 4 and Table 3 suggests that the reform helped Odense to attract students with higher completion rates, which suggests that Odense was making admission decisions under incomplete information in the pre-reform years.

Adverse Selection at Aarhus: To provide more direct evidence for the presence of inter-dependent values, we turn to the spillover effects of Odense's admission reform on dropout rates at Aarhus' medical program. Specifically, we split enrolled students at Aarhus by their reported preference ranking, which programs cannot use in their admission decisions, to test for an increase in adverse selection at Aarhus after the reform. Dropout rates among students whose first choice is Aarhus are not affected by Odense's information experiment and provide a natural control group. In contrast, students who prefer Odense over Aarhus will only enroll at Aarhus if they were rejected by Odense. Hence, these students may be adversely selected particularly so after the admission reform.

Figure 4b presents the residual dropout rate, after controlling for year and GPA fixed effects, among enrolled students in Aarhus by their reported first preference among medical programs. We focus the graphical discussion on the comparison of average pre- and post-reform dropout rates, denoted by the blue and red bars, due to sample size limitation that make it difficult to test for parallel trends in the pre-period. Additional evidence on the corresponding time series is provided in Appendix Figure 18. For students who prefer Aarhus, we see stable outcomes over time. We also find consistently higher dropout rates pre- and post-reform among Aarhus students whose first preference was Copenhagen medical school, consistent with a stable degree of adverse selection among these candidates. This stands in sharp contrast to persistence for students at Aarhus who prefer Odense but were not admitted to Odense. Following the reform, we see a striking increase in dropout rates of more than 10 percentage points, providing first evidence for an increase in adverse selection. At the same time, Figure 4b further shows that the University of Southern Denmark in Odense faced the highest residual dropout rates in the pre-reform period among students who would have preferred a rival program at Aarhus or Copenhagen. But for these applicant groups, Odense achieved the largest reduction in dropouts after their screening reform.

To quantify the impact of the reform on Aarhus' dropout rate more formally, we compare dropout rates by program preference before and after the reform using a difference-in-differences research design. Specifically, we estimate the following regression model:

$$Y_{it} = \alpha_0 + \alpha_1 \cdot Prefer_Odense_i + \alpha_P \cdot Post_t + \alpha_{DID} \cdot Prefer_Odense_i \cdot Post_t + \epsilon_{it} \quad (4)$$

for student i admitted in year t, where $Prefer_Odense$ is an indicator that turns on if i

prefers Odense over Aarhus.

Table 4 presents estimates of the key parameter of interest α_{DID} for admitted students to Aarhus in the first row. We find that the 3-year dropout rate of students who prefer Odense increases by 11.8 p.p. in the post-reform period, relative to students who prefer Aarhus, see column 1. This result includes student outcomes at any college program they may enroll in. The point estimate increases slightly when refining the sample to students who enroll in any medical school program, column 2, or ever enrolled at Aarhus, column 3. The point estimate remains at 12 p.p. higher dropout rates when only considering students who enroll in the same year at Aarhus medical school, see column 4. These results suggest a substantial increase in adverse selection among admitted students at Aarhus after Odense's admission reform.

Discussion: The decline in dropout rates at Odense, Figure 4a, and the increase in dropout rates Aarhus among students who prefer Odense over Aarhus, Figure 4b, is consistent with interdependent program values. Odense is able to reject less talented students in the post-reform period, which then contribute to a winner's curse at Aarhus. We note, however, that the reform may have affected the composition of quota 2 applicants that may have contributed to the observed changes in dropout rates. Specifically, students with moderate program preferences for Odense may have refrained from applying to Odense via quota 2 if the increased screening efforts increased the application costs from the student's perspective. If student preferences are positively correlated with talent, then this may result in an advantageous student selection at Odense. If preferences are also positively correlated between programs, then this may also result in an adverse student selection at Aarhus.[19] To conclude, the presented evidence suggests that Aarhus could reduce their post-reform dropout rates if Aarhus knew and acted on the information on completion rates possessed by Odense and students. This suggests that the information structure is one of interdependent values.

5.3 Program Admission Preferences and the Home Bias

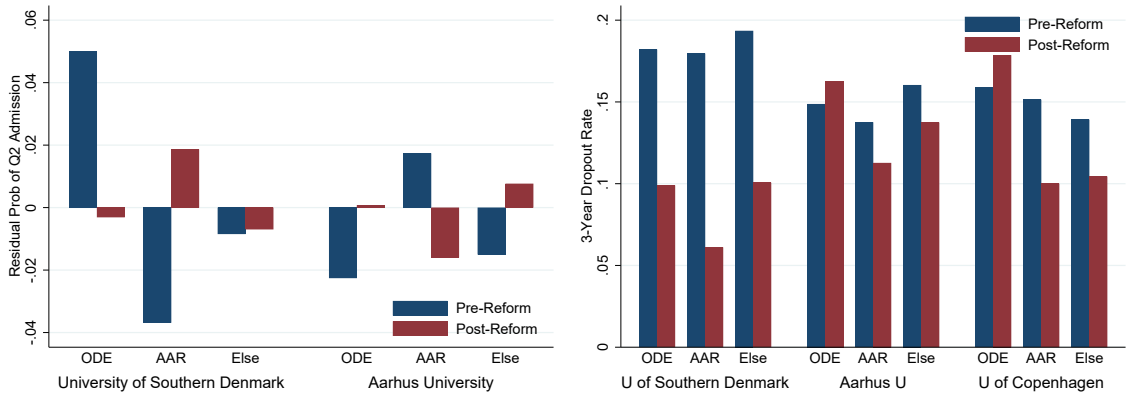
Building on these insights, we next explore whether program's student rankings are consistent with interdependent values.

While programs cannot condition on applicants' preference rankings, they can condition on their former residence which is a predictor of student preferences as discussed earlier and seen in Figure 1a. In Figure **??** we consider the probability of being ranked in the top 50 percent among all Quota 2 applicants above the quota 2 admission bar depending on the

[19] Alternatively, students with lower expected completion rates may have expected a decline in their admission chance, following the improved screening, and may have then decided to not apply at all. We note, however, that Odense significantly increased their quota 2 admission rates, which may have increased the admission chances for some lower skilled students on net.

student's region of residence, after controlling for fixed effects for student gpa by cohort. Starting with admissions to Odense, indicated by the left half of the graph, we see clear evidence for a home bias in the pre-reform years, denoted in blue. Students from Odense have the highest chances of being ranked among top quota 2 applicants. Conversely, students from Aarhus have the lowest chances. This pattern is reversed (at smaller magnitudes) in the post-reform years; now students from Aarhus have the highest chance of receiving a top ranking. This behavior is consistent with interdependent program values but also with changes in self-selection of students in response to changes in application costs as discussed above. In both cases, Odense may consider predictors of student preferences in their ranking decisions but less so in the post-reform years as Odense collects a more informative signal of student persistence.

Figure 5: Program Preferences and Quota 2 Applications



(a) Quota 2 Top 50 Rank Chance (b) Dropouts by Former Residence

Note: The left figure presents the residualized share of quota 2 applicants that are in the top 50 percent among all applicants above the quota 2 score cutoff, after controlling for cohort-gpa fixed effects.

Turning to Aarhus, we also find evidence for a home bias in the pre-reform years as indicated in the right part of Figure **??**. Students from Aarhus have the highest chances of being ranked among the top applicants when compared to students from Odense and other regions. This bias flips sign in the post-reform years, and Aarhus now favors students from other regions. Students from Odense no longer receive a penalty in the post-reform period to be placed in a top 50 spot, but additional analysis shows that they remain at a similar disadvantage as in the pre-reform period to be ranked above the quota 2 admission bar at all, see Figure 19e. While the pre-reform evidence for admissions to Aarhus is consistent with interdependent values, the change in admission chances pre-post does not point in the expected direction. This could be because Aarhus is not responding strategically to changes in Odense's signal precision and or Aarhus experiences concurrent changes in the composition of applicants.

In Figure 5b, we compare dropout rates by region of origin over time. Consistent with the evidence presented above, we see a decline in dropout rates in Odense following the reform. At Aarhus, we see a decline in dropout rates among students admitted from Aarhus and elsewhere, but an increase in dropout rates among students from Odense. This suggests that Aarhus could have reduced their post-reform dropout rates, by increasing their admission shares for students from Aarhus or elsewhere, a point that we return to below.

5.4 Interdependent Program Values

The former discussion highlights the empirical challenges in distinguishing between two different sources of interdependent values: interdependent program values and student self-selection.

To isolate interdependent program values, we return to programs' ranking of students that holds the composition of quota 2 applicants fixed. Specifically, we assess the relative screening precision of the two medical programs at Aarhus and Odense that are closest substitutes by analyzing students who apply through quota 2 to both programs. To this end, we focus on a pairwise comparison of these applicants and compare the relative ranking of the two programs over the applicant pair. For any pair of applicants in a given cohort, we construct two indicators that turn on if Odense ranks student 1 above student 2 and if Aarhus ranks student 1 above student 2. This relative assessment of student quality extends the analysis using safe admissions, rank bins or percentiles and offers two important advantages. First, we can exploit the full information contained in the rankings and second, we do not need to impose assumption on how ranks and percentiles compare between programs in a given cohort.

The dependent variable is the relative comparison of dropout outcomes, which equals 1 if student 1 drops out and student 2 does not. The outcome equals 0 if both students or none of them drops out and finally the outcome equals -1 if student 2 drops out and student 1 does not. We then regress this relative dropout measure on the ranking indicators, controlling for cohort fixed effects, resident location fixed effects, and GPA fixed effects. We account for the correlation patterns in the dyadic data by employing a two-way clustering at the individual level.

The results in Table 5, column 1, first show that Aarhus and Odense rarely agree on the relative ranking of two candidates. The effect of Odense's ranking on Aarhus' ranking is positive and statistically significant, but Odense ranking one student over the other student increases the odds that Aarhus does the same by only 5.8 p.p. This discrepancy allows us to analyze the relationship between program rankings and student persistence. Tracking dropouts at any program a student enrolls in, column 2 shows that the relative ranking by

Table 5: Quota 2 Ranking and Student Dropout Rates: Pairwise Comparisons

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	AAR 1>2	Difference in 3Y Dropout for Student 1 versus Student 2				
Sample	All	All	Both ODE	None ODE	Pre-2002	Post-2002
ODE Ranks 1>2	0.058***	-0.116***	-0.033*	-0.054**	-0.060*	-0.119***
	(0.017)	(0.017)	(0.018)	(0.025)	(0.033)	(0.019)
AAR Ranks 1>2		-0.015	-0.013	-0.034	0.010	-0.018
		(0.016)	(0.018)	(0.027)	(0.036)	(0.017)
Observations	67,992	67,992	21,725	14,679	6,488	61,504
R-squared	0.035	0.070	0.087	0.092	0.083	0.080

*Note: Table 5 analyzes Aarhus' and Odense's relative quota 2 rankings for pairs of quota 2 applicants to both programs. "ODE Ranks 1>2" is an indicator variable that takes value 1 if Odense assigns a higher quota 2 rank to candidate 1 than to candidate 2, and analogously for "AAR Ranks 1>2". Column 1 regresses the two relative assessments on each other. The outcome of columns 2-6 is the difference in 3-year dropout rates within the pair, that is the outcome is 1 if candidate 1 drops out of their study program but candidate 2 persists, 0 if none of both candidates persist, and -1 if only candidate 2 drops out. All regressions control for cohort fixed effects, resident location fixed effects, and GPA fixed effects. Standard errors reported in parentheses use two-way clustering at individual applicant level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Odense is strongly associated with relative student performance conditional on the ranking by Aarhus. Conversely, Aarhus' assessment does not explain dropout outcomes conditional on the ranking by Odense and observable characteristics. In column 3, we restrict the observations to pairs of students that both enroll at Odense. We again find that Odense ranking predicts dropouts conditional on Aarhus signal. This is also the case when restricting attention to pairs of students that both enroll in other programs than Odense, see column 4. Finally, we split the full sample of pairs between the pre- and post reform period, see columns 5 and 6. For Odense, the coefficient increases from 6 p.p. to 11.9 p.p. in the post-reform period, and becomes significant at the 1% level. Yet, because of smaller sample size in the pre-2002 period, we are slightly underpowered to reject that the two coefficients are the same. For Aarhus, we find a small improvement over time but post-reform screening remains at a small coefficient of 1.8 p.p. that is statistically insignificant.

We further analyze Odense's screening precision using analogous pairwise regressions for applicants who apply to both Copenhagen and Odense, or to Copenhagen, Odense, and Aarhus, in Appendix Table 16. While we find significant predictive power of Copenhagen's signal for student outcomes, Odense's signal remains highly informative conditional on information by one or both rivals. Results in all subsamples are consistent with an improvement in information quality at Odense after their screening reform.

Overall, our findings indicate that Odense holds private information that predicts dropout outcomes at Odense and elsewhere, even when conditioning on the information held by its rivals. In other words, this suggests that especially Aarhus as the closest substitute program

could reduce their dropout rates if Aarhus knew and acted on the information on completion rates possessed by Odense and provides evidence for interdependent program values. In addition, our findings suggest that Odense's informational advantage about completion increases significantly in the post-reform period.

5.5 Self-Selection

To isolate the effects of student selection, we focus on quota 1 admissions that are entirely based on the student's GPA and explore the correlation between student preferences, the decision to apply via quota 2, and program dropout rates. Table 6 presents the results from a linear regression of the three year dropout rate on a quota 2 indicator, that turn on if the student applied via quota 2, and a preference indictor that turns on if the student ranked at least one of the two rival medical program higher that the program they enrolled in. We find that students who also applied via quota 2 have a 2.4 percentage points lower 3-year dropout rate, see column 1. The result remains largely unchanged when excluding transfers, column 3, or controlling for location and GPA, columns 2 and 4. We also find similar results when looking at completion rates in columns 5 and 6 but we do not find differences in average study time until graduation among graduates who had applied via quota 2.

Table 6: Self-Selection and Dropouts Among Quota 1 Applicants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	3Y Dropout		3Y Drop excl Transfers		Completion		Time Until Completion	
Applied Quota 2	-0.024**	-0.021*	-0.021**	-0.021*	0.019	0.030*	-19.046	-20.880
	(0.010)	(0.011)	(0.010)	(0.011)	(0.014)	(0.016)	(15.902)	(17.746)
Prefer Other Prog	0.041***	0.008	0.017	-0.009	0.001	0.043**	50.029**	16.712
	(0.013)	(0.016)	(0.013)	(0.016)	(0.017)	(0.021)	(19.594)	(24.026)
Constant	0.127***	0.128***	0.119***	0.120***	0.836***	0.833***	2,593.385***	2,594.934***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(4.858)	(5.049)
Add Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	12,068	12,068	12,068	12,068	8,692	8,692	7,284	7,284
R-squared	0.008	0.076	0.007	0.074	0.004	0.088	0.064	0.152

*Note: This table presents the effects of applying via quota 2 and preferring a different medical program on outcomes among students admitted via quota 1. The sample includes students enrolled in either Aarhus or Odense medical school through quota 1 admission. Even columns include year and program fixed effects. Odd columns include program-year fixed effects, program-location-of-residence fixed effects, and GPA fixed effects. Columns 1-4 report results for the 3-year dropout rates, and columns 3 and 4 exclude transfers. Columns 5 and 6 report completion rates for cohorts starting in 1994-2009. Columns 7 and 8 report study time to completion for graduates from cohorts 1994-2009. Odd columns control for year by school FE, even columns add controls for gpa as well as location by school FE. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Admitted students who prefer the rival program have higher dropout rates and longer study times, see the second row. In contrast to the evidence on the decision to apply via quota 2, these effects become statistically insignificant after controlling for location of

residence and GPA, see columns 2 and 8. Together these regressions present evidence for self-selection that operates through observable and unobservable student characteristics.

6 Structural Model

Building on theoretical discussion and the empirical evidence, we now specify our empirical model that allows us to quantify the information structure more precisely and to evaluate counterfactual policy experiments. We focus on two programs, Odense and Aarhus and two time periods, pre=1994-2001 and post=2002-2013. Signals are private to programs, and preferences and application cost shocks are private to students. We assume that there are commonly observed student attributes X including GPA, GPA interacted with a rival region indicator, and two student region of origin fixed effects (considering three potential regions). For the structural estimation, we aggregate the student GPA into four bins to reduce the observable type space and hence the computational complexity. Our revised GPA measure varies from 0 to 3 for low to very high GPAs.[20]

6.1 Talents, Signals, and Payoffs

Talents: Latent student talents are denoted by $\tilde{\omega}_j$. They are correlated between programs and distributed according to:

$$\begin{pmatrix} \tilde{\omega}_1 \\ \tilde{\omega}_2 \end{pmatrix} \sim F_{\tilde{\omega}_1,\tilde{\omega}_2} \ . \tag{5}$$

Dropouts: Students persist at (do not drop out from) program j if they enroll at j and have

$$\omega_j^* \equiv X_j'\alpha_j + \tilde{\omega}_j > 0. \tag{6}$$

Here, X is an observed 5-dimensional vector including a constant term, GPA, GPA interacted with a rival region indicator, and two student region of origin fixed effects (considering three potential regions).

Program Signals: Program j receives a conditionally-independent private signal of student talent $\tilde{\omega}_j$ for each quota 2 applicant. We assume that signals are normally distributed conditional on talent:

[20] Our revised GPA measure is defined as follows: 0 if gpa $\leq$ 8.8, 1 if 8.8<gpa$\leq$9.5, 2 if 9.5<gpa$\leq$9.8, 3 if gpa >9.8. It captures differences in quota 2 application behavior shown in Figure 1b and difference in quota 1 admission chances given by the GPA cutoff described in Appendix Figure 16e. See Appendix Table 20 for more details.

$$\begin{pmatrix} s_1 \\ s_2 \end{pmatrix} |\tilde{\omega} \sim N(\begin{pmatrix} \rho_{1t} \cdot \tilde{\omega}_1 \\ \rho_{2t} \cdot \tilde{\omega}_2 \end{pmatrix}, \begin{pmatrix} 1-\rho_{1t}^2 & 0 \\ 0 & 1-\rho_{2t}^2 \end{pmatrix}) \ . \tag{7}$$

Here, ρ_{jt} denotes the correlation between j's signal and talent $\tilde{\omega}_j$, which may vary between the pre- and post reform period indexed by $t \in \{pre, post\}$.

Program Payoffs: Next, we define program payoffs, which depend on program persistence, ω_j^*, and on other characteristics X, which may capture non-dropout related preferences such as a preference for locals. Specifically, when a student enrolls in program j, the program receives a payoff

$$\omega_j = \omega_j^* + \pi_j(X) \tag{8}$$

from this student, where $\pi_j(X)$ denotes the preference over other characteristics.

Utilities: Turning to applicants, if a candidate enrolls in j he receives utility

$$u_j = X_j' \gamma_j + \epsilon_j^u, \tag{9}$$

where ϵ_j^u is a student preference shock. We assume that preference shocks are normally distributed conditional on talent:

$$\begin{pmatrix} \epsilon_1^u \\ \epsilon_2^u \end{pmatrix} |\tilde{\omega} \sim N(\begin{pmatrix} \rho_{\epsilon 1} \cdot \tilde{\omega}_1 \\ \rho_{\epsilon 2} \cdot \tilde{\omega}_2 \end{pmatrix}, \begin{pmatrix} 1-\rho_{\epsilon 1}^2 & \rho_u \cdot \sqrt{1-\rho_{\epsilon 1}^2} \cdot \sqrt{1-\rho_{\epsilon 2}^2} \\ \rho_u \cdot \sqrt{1-\rho_{\epsilon 1}^2} \cdot \sqrt{1-\rho_{\epsilon 2}^2} & 1-\rho_{\epsilon 2}^2 \end{pmatrix}) \ , \tag{10}$$

where $\rho_{\epsilon j}$ denotes the correlation between the student preference shock and talent and ρ_u denotes the correlation between preference shocks, conditional on talent.

Application Costs: Quota 1 applications are free but quota 2 applications are costly. We measure quota 2 application costs, $c_{\{j\}}$, in utility units and assume that they are normally distributed and independent of talent:

$$\begin{pmatrix} c_{\{1\}} \\ c_{\{2\}} \end{pmatrix} \sim N(\begin{pmatrix} \delta_{1t} \\ \delta_{2t} \end{pmatrix}, \begin{pmatrix} \sigma_{ct}^2 & \sigma_{c12t} \\ \sigma_{c12t} & \sigma_{ct}^2 \end{pmatrix}) \ , \tag{11}$$

where δ_{jt} and σ_{ct}^2 denotes mean and variance of applications costs. σ_{c12t} denotes the covariance between application costs. These parameters are allowed to vary between the pre- and post reform period. We abstract away from returns to scale in application costs and assume $c_{\{1,2\}} = c_{\{1\}} + c_{\{2\}}$.

6.2 Strategies

Applications: As outlined in Section 3, students apply via quota 1 to program j if $u_j > 0$. They also rank programs truthfully, i.e. put j above j' whenever $u_j > u_{j'}$.

Once students learn which programs j satisfy $u_j > 0$, they investigate these programs and learn quota-2 application costs only for these programs. Students choose a subset of their quota 1 applications to which to apply to via quota 2, in order to maximize their expected utility net of application costs. The expected utility depends on the quota 1 and the quota 2 admission chance, which we detail in Appendix Section D.

Quota 2 Admissions: Building on Proposition 1, students are admitted to j via quota 2 if they apply via quota 2 to j, are not admitted to any program they rank higher, and have $s_j > \underline{s}_{jt}(X)$, where $\underline{s}_{jt}(X)$ is the (endogenous) program cutoff and s_j is program j's signal of student talent. We estimate flexible program cutoffs

$$\underline{s}_{jt}(X) = X_j'\beta_{jt}, \tag{12}$$

where $t \in \{pre, post\}$ denotes the time period. The cutoff defines an implicit reservation value per seat $\underline{V}_{jt}$ and programs admit students if and only if their expected payoff, conditional on accepting the offer, is greater than this reservation value. Formally, that means that

$$E(\omega_j | D_j^2(X), s_j = \underline{s}_{jt}(X)) = \underline{V}_{jt} \ . \tag{13}$$

where $D_j^2(X)$ denotes student demand for quota 2: students with observables X that would match with program j via quota 2 if they are admitted.

Safe Quota 2 Admissions: We estimate a separate program cutoff for safe admissions, defined as those applicants that are ranked within the K_{jt} first positions on the program ranking, where K_{jt} denotes the program's capacity of quota 2 seats in the given year. Specifically, we estimate the following cutoffs:

$$\underline{s}_{jt}^{SAFE}(X) = X_j'\beta_{jt}^{SAFE} \ . \tag{14}$$

Note, that only the overall program cutoffs outlined in equation (12) affect the student's admission chances and hence enter their expected utility, see Appendix Section D. Likewise, only the overall program cutoff affects the program's payoffs.

7 Estimation and Results

7.1 Estimation Strategy

Estimation proceeds in two steps. We first estimate admissions cutoffs and the joint distribution of parameters governing utilities, signals, and graduation propensities, jointly, following the sequential E-M approach in Arcidiacono and Jones (2003). We then use these estimates to decompose programs' cutoffs and recover programs' non-graduation-related preferences $\pi(\cdot)$.

7.1.1 Estimating parameters and cutoffs

We consider a sample of N applicants and a vector of observable applicant characteristics y, which includes dropout outcomes, quota 1 applications, quota 2 applications, and quota 2 admissions by program. We discretize the support of the talent distribution $F_{\tilde{\omega_1},\tilde{\omega_2}}$ into K distinct types and denote by p_k the unconditional probability that an applicant belongs to type k. The discretized support also imposes a required scale normalization on the distribution of talents. The vector of probabilities is given by $p = (p_1, ..., p_K)$ with $\sum_{k=1}^{K} p_k = 1$. We let Θ denote the vector of structural parameters and let h_k denote the density function for type k. The unconditional (with respect to k) likelihood of y_i is then

$$g(y_i; \Theta, p, x_i) = \sum_{k=1}^{K} p_k \cdot h_k(y_i; \Theta, x_i) \ .$$

Leveraging the conditional independence assumption on program signals, we can decompose the type-conditional likelihood function as:

$$h_k(y_i; \Theta, x_i) = h_k^1(y_i^1; \Theta_1, x_i) \cdot h_k^2(y_i^2; \Theta_1, \Theta_2, x_i)$$

where y_i^1 is only comprised of dropout outcomes and quota 2 admissions (including safe quota 2 admission). Similarly, $\Theta_1 = \{\alpha_j, \beta_{jt}, \beta_{jt}^{SAFE}, \rho_{jt}\}$ comprises only the structural parameters governing dropout and quota 2 admission outcomes. y_i^2 denotes student's quota 2 application decisions and their preference ranking. Accordingly, $\Theta_2 = \{\gamma_j, \rho_{\epsilon j}, \delta_{jt}, \sigma_{ct}, \sigma_{c12t}\}$ comprises the structural parameters governing preferences and quota 2 application costs. In our model, conditional on type, dropout outcomes and quota 2 admissions do not depend on preferences, which is why Θ_2 does not enter h_k^1. Of course outcomes y_i^1 will be censored if students didn't apply to the respective program. The reverse is not true because the quota 2 admission chances affect the optimal quota 2 application portfolio.

To reduce computational complexity, we follow Arcidiacono and Jones (ibid.) and estimate the model via generalized method of moments (GMM). The population moment conditions for $\Theta = \{\Theta_1, \Theta_2\}$ and p are given by:

$$E_{y,x}\begin{pmatrix} \sum_{k=1}^{K} Pr[k|y,\Theta^*,p^*,x]\cdot\frac{\partial ln(h_k^1(y^1;\Theta_1^*,x))}{\partial\Theta_1} \\ \sum_{k=1}^{K} Pr[k|y,\Theta^*,p^*,x]\cdot\frac{\partial ln(\cdot h_k^2(y^2;\Theta_1^*,\Theta_2^*,x))}{\partial\Theta_2} \\ Pr[1|y,\Theta^*,p^*,x]-p_1^* \\ . \\ . \\ . \\ Pr[K|y,\Theta^*,p^*,x]-p_K^* \end{pmatrix} = 0\ . \tag{15}$$

Here, $Pr[k|y,\Theta,p,x]$ denotes the conditional probability that an applicant is of type k, conditional on observing y and x. It follows from Bayes rule that $Pr[k|y,\Theta,p,x]$ is given by:

$$Pr[k|y_i,\Theta,p,x_i] = \frac{p_k\cdot h_k(y_i;\Theta,x_i)}{g(y_i;\Theta,p,x_i)}. \tag{16}$$

The sample analogue to equation (15) is given by

$$\frac{1}{N}\sum_{i=1}^{N}\begin{pmatrix} \sum_{k=1}^{K} Pr[k|y_i,\Theta^*,p^*,x_i]\cdot\frac{\partial ln(h_k^1(y_i^1;\Theta_1^*,x_i))}{\partial\Theta_1} \\ \sum_{k=1}^{K} Pr[k|y_i,\Theta^*,p^*,x_i]\cdot\frac{\partial ln(\cdot h_k^2(y_i^2;\Theta_1^*,\Theta_2^*,x_i))}{\partial\Theta_2} \\ Pr[1|y_i,\Theta^*,p^*,x_i]-p_1^* \\ . \\ . \\ . \\ Pr[K|y_i,\Theta^*,p^*,x_i]-p_K^* \end{pmatrix} = 0\ . \tag{17}$$

7.1.2 Computational Details

The estimation takes a sequential E-M approach following Arcidiacono and Jones (2003), which we summarize below. More details are provided in Appendix Section **??**.

The estimation proceeds in two M steps and one E step. We start each iteration l with a guess of the unconditional type weights, $\hat{p}^l = (\hat{p}_1^l, ..., \hat{p}_K^l)$, and the structural parameters $\hat{\Theta}^l$. Each iteration then completes the following three steps:

1. **M1 Step:** We update our estimate of Θ_1 by solving

$$\widehat{\Theta_1}^{l+1} = \underset{\Theta_1}{\text{argmax}} \sum_{i=1}^{N}\sum_{k=1}^{K} Pr[k|y_i,\hat{\Theta}^l,\hat{p}^l,x_i]\cdot ln(h_k^1(y_i^1;\Theta_1,x_i))\ , \tag{18}$$

   where $Pr[k|y_i,\hat{\Theta}^l,\hat{p}^l,x_i]$ is calculated based on equation (16).

2. **M2 Step:** Building on step M1, we update our estimate of Θ_2 by solving

$$\widehat{\Theta_2}^{l+1} = \underset{\Theta_2}{\text{argmax}} \sum_{i=1}^{N} \sum_{k=1}^{K} Pr[k|y_i, \hat{\Theta}^l, \hat{p}^l, x_i] \cdot ln(h_k^2(y_i^2; \widehat{\Theta_1}^{l+1}, \Theta_2, x_i)) \ . \tag{19}$$

3. **E Step:** Finally, we update the unconditional weights according to

$$\widehat{p_k}^{l+1} = \frac{1}{N} \sum_{i=1}^{N} Pr[k|y_i, \hat{\Theta}^{l+1}, \hat{p}^l, x_i] \ . \tag{20}$$

We iterate over steps 1-3 until changes in parameters and weights between iterations fall in a small tolerance range.

7.1.3 Program Objectives and Admission Cutoffs

We decompose programs' cutoffs as follows. Without loss, we may pick some x_0 such that $\pi_j(x_0) = 0$.At the cutoff, assuming monotone and continuous strategies, we have

$$E(\omega_j|D_j(x), s_j = \underline{s}_j(x)) = E(\omega_j^*|D_j(x), s_j = \underline{s}_j(x)) + \pi_j(x). \tag{21}$$

Hence we have:

$$\pi_j(x) = E(\omega_j^*|D_j(x), s_j = \underline{s}_j(x)) - E(\omega_j^*|D_j(x_0), s_j = \underline{s}_j(x_0)). \tag{22}$$

We use the estimates from the first estimation step to calculate $E(\omega_j^*|D_j(x), s_j = \underline{s}_j(x))$. To do so, for quadrature points $\omega_j^{(m)}$ we compute

$$f(\omega_j^{(m)}|s_j = \underline{s}_j(x))$$

and simulate $Pr(D_j(x)|\omega_j = \omega_j^{(m)}, s_j = \underline{s}_j(x))$ by accept/reject sampling.

7.2 Results

Table 7 presents the preliminary model estimates, which we discuss in detail below. We start with a discussion of parameters and cutoffs before turning to the program objectives.

7.2.1 Preferences, Dropouts, Quota 2 Applications, and Quota 2 Cutoffs

Dropouts: Panels A and B present the parameter estimates on persistence (not dropping out), see equation (6). Empty cells in the post-period imply that the parameter estimate applies to both pre- and post-period as discussed above. Our results suggests that ignoring selection on unobservables, local students generally have the lowest dropout rates conditional

Table 7: Model Estimates

	Pre Reform		Post Reform	
	Parameter	Standard Error	Parameter	Standard Error
A. Persist Odense				
Constant	-0.001	0.066		
GPA	-0.069	0.032		
GPA × From Aarhus	-0.320	0.086		
From Odense	0.390	0.068		
From Aarhus	0.393	0.129		
B. Persist Aarhus				
Constant	0.412	0.055		
GPA	0.087	0.021		
GPA × From Odense	0.071	0.074		
From Odense	0.118	0.145		
From Aarhus	0.318	0.045		
C. Quota 2 Admission Odense				
Constant	1.915	0.216	0.499	0.081
GPA	0.140	0.332	-0.022	0.037
GPA× From Aarhus	-0.832	0.539	0.062	0.084
From Odense	0.309	0.387	-0.023	0.073
From Aarhus	0.389	0.416	0.099	0.094
D. Quota 2 Safe Admission Odense				
Constant	-0.446	0.126	-0.378	0.082
GPA	0.371	0.097	0.030	0.033
GPA× From Aarhus	-0.150	0.197	0.001	0.073
From Odense	0.202	0.111	0.028	0.067
From Aarhus	-0.055	0.150	0.206	0.083
E. Quota 2 Admission Aarhus				
Constant	1.027	0.102	-0.881	0.040
GPA	0.676	0.114	0.141	0.018
GPA× From Odense	-0.233	0.280	-0.070	0.081
From Odense	-0.012	0.212	0.158	0.102
From Aarhus	0.246	0.113	0.128	0.037
F. Quota 2 Safe Admission Aarhus				
Constant	-0.445	0.079	-2.046	0.065
GPA	0.057	0.055	0.242	0.029
GPA× From Odense	0.026	0.177	-0.168	0.123
From Odense	-0.305	0.171	0.104	0.172
From Aarhus	-0.063	0.074	0.077	0.063
G. Utility Odense				
Constant	-0.099	0.007		
GPA	-0.295	0.005		
GPA× From Aarhus	-0.106	0.007		
From Odense	0.703	0.014		
From Aarhus	0.087	0.012		
H. Utility Aarhus				
Constant	-0.010	0.007		
GPA	-0.063	0.005		
GPA× From Odense	0.033	0.012		
From Odense	-0.060	0.016		
From Aarhus	1.109	0.015		
I. Quota 2 Application Costs				
Mean Cost Odense: δ_{Ode}	0.841	0.032	2.311	0.083
Mean Cost Aarhus: δ_{Aar}	0.734	0.022	0.793	0.035
Correlation in Cost Shocks: σ_{c12}/σ_c^2	0.582	0.031	0.509	0.017
Variance in Cost Shocks: σ_c^2	0.547	0.045	2.586	0.240
J. Information Structure				
Correlated Talents: $corr(\tilde{\omega_1}, \tilde{\omega_2})$	0.793			
Signal Quality Odense: ρ_{Ode}	0.059	0.059	0.191	0.041
Signal Quality Aarhus: ρ_{Aar}	0.000	0.053	0.000	0.030
Preference Signal Odense: $\rho_{\epsilon,ODE}$	0.474	0.011		
Preference Signal Aarhus: $\rho_{\epsilon,AAR}$	0.268	0.013		
Preference Correlation: ρ_u	0.529	0.000		

*Note: This table presents the structural parameter estimates. Empty cells in the post-period imply that the parameter estimate applies to both pre- and post-period. 95% confidence intervals in brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

on GPA, which ranges from 0 for low GPAs to 3 for high GPAs as discussed above.[21] Dropout rates decrease in the student GPA at Aarhus but interestingly not at Odense. The evidence on Odense is consistent with the upward sloping dropout gradients in GPA shown for quota 2 admission shown in Figure 17b and may help reconcile why quota 2 admission chances to Odense are not systematically related to the GPA, Figure 17a, which we return to below. Importantly, we find evidence for correlated student outcomes between programs, conditional on observables. The correlation between unobserved student talents equals 0.79, see panel J. That said, aptitude for one program does not perfectly predict aptitude for the other program, allowing for some program-specific match values.

Quota 2 Admissions: Panels C and D present the parameter estimates for the quota 2 admissions cutoff, see equation (12), and the more competitive cutoff for safe admissions at Odense, see equation (14). In the pre-reform period, students from Odense have the highest chance of being admitted and making it into the safe admission seats, conditional on GPA, except for students with the lowest GPA=0 in panel C. Here, students from Aarhus have a slight advantage. Overall, this points to an important home bias in the admission decisions in the pre-reform period. However, and consistent with the earlier evidence from Figure **??**, we find that conditional on GPA, the quota 2 admission chance of students from Odense (and the chance of making it into the safe seats) falls in the post-reform period. Students from Aarhus now have the highest chance of being admitted via quota 2 and making it into the safe seats.

Importantly, and consistent with our earlier evidence, our findings from panel J suggest that Odense's signal carries information on student talents both in the pre- and the post-reform period, see coefficient ρ_{Ode}. The point estimate is relatively small and not statistically significant in the pre-reform period 5.9 p.p. (se=5.9 p.p). In the post-reform period, the signal precision increases as evidenced by a higher correlation of 19.1 p.p. (se=4.1 p.p.). This suggests that Odense's admission reform allowed Odense to reject less talented students in the post-reform period. In combination with the positive correlation in talents across programs, this provides evidence for interdependent program values.

Finally, and following up on the former dropout discussion, we find no systematic relationship between student GPA and admission chances to Odense, see Panel C. We do find evidence for a positive relationship between GPA and being above the safe admissions cutoff in the pre-reform period, which however fades away in the post-reform period as Odense's

[21] There are two exceptions. The first concerns students in the lowest GPA bin at Odense. Here students from Aarhus are slightly more likely to persist than students from Odense, coefficient of 0.393 vs. 0.39. The second concerns students in the highest GPA bin at Aarhus. Here, students from Odense are slightly more likely to persist than students from Aarhus, coefficients of 0.118+3*0.071=0.338 vs. 0.318. Both of these difference are not statistically significant.

become better at screening applicants.

Panels E and F present analogous evidence for admissions to Aarhus. The pre-reform coefficients point to a home bias for Aarhus students in overall admissions, whereas students from regions other than Odense and Aarhus (the excluded group) have slightly higher chances of placement into the top seats. After the reform, overall admission chances for students from Odense improve, whereas chances for students from Aarhus decrease, see panel E, mitigating the home bias seen in the pre-reform years. Turning to Aarhus' signal precision, we find no evidence that Aarhus learns some information on unobserved student talent in the pre- or post-reform period, see coefficient ρ_{Aar} in panel J. These findings suggest that Odense was significantly better at learning about unobserved student talents in the post-reform period.

Preferences: The second channel that can contribute to changes in dropout rates over time is student self-selection, which we turn to next. Consistent with the descriptive evidence, we find evidence for a home bias in student preferences, see panels G and H. Students from Odense have the highest utility from attending Odense and similarly students from Aarhus have the highest utility from attending Aarhus. We find a positive correlation between preference shocks, $\rho_u = 0.529$, and a positive correlation between preference shocks and talents for both Odense, $\rho_{Ode} = 0.474$, and Aarhus $\rho_{Aar} = 0.268$, see panel J. This provides evidence that students hold private information on dropout outcomes. Our results also allow for complex forms of student selection through the costly quota 2 application process, which we turn to next.

Quota 2 Applications: We find significant average quota 2 application costs for both programs, which increase substantially after the reform in Odense, but remain relatively stable at Aarhus. This is consistent with the higher burden of the extended review process. At the same time, we see an increase in the variance of quota 2 application costs. Combined with the evidence from panel J, this suggests that the pool of quota 2 applicants at Odense will be advantageously selected after the reform. Students with weak preferences for Odense will shy away from applying to Odense, who have on average higher dropout rates. In contrast, these students may apply to Aarhus contributing to an adversely selected applicant pool at Aarhus.

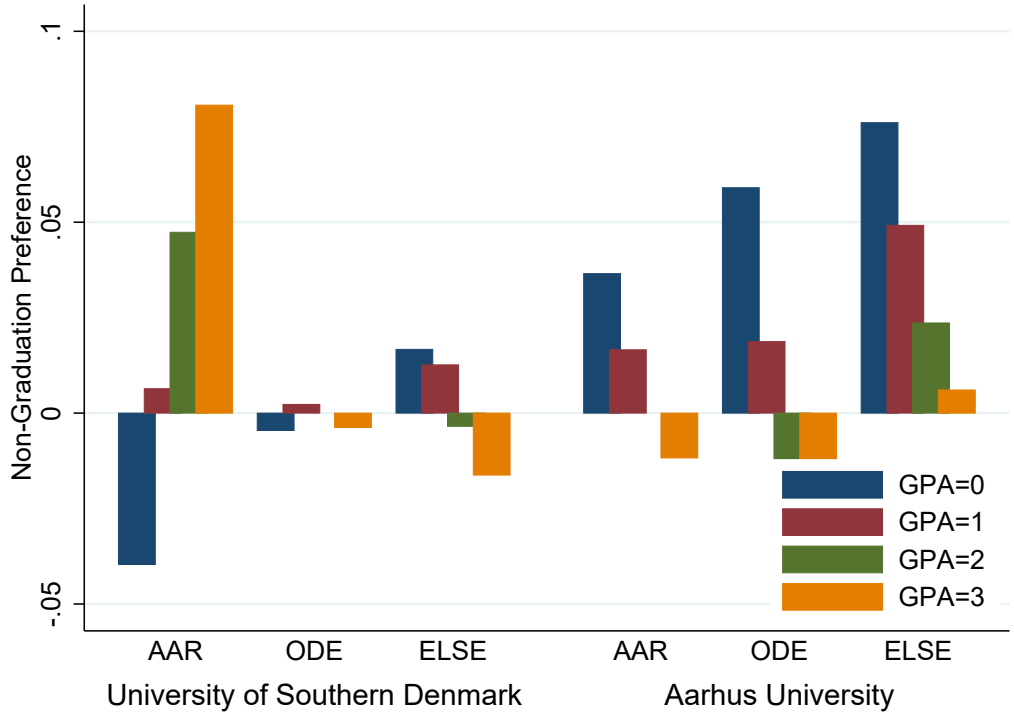
7.2.2 Program Objectives in the Post-Period

Next, we decompose program objectives following the procedure described in section 7.1.3. Specifically, we use our model estimates summarized above to determine marginal dropout rates for students admitted via quota 2 by their origin and GPA. We can then apply equation (22) to analyze programs' non-dropout preferences over these varying student characteristics.

Figure 6 summarize the estimated non-graduation preferences, $\pi(x)$, by program, student

gpa, and the student's former region of residence in the post-reform period. As a normalization, we choose type x_{0j} to be local applicants from region j in GPA group 2. Hence, all estimates are relative to these program-specific baseline groups, respectively. A full overview of the estimates is presented in Appendix Table **??**.

Figure 6: Non-Graduation Preferences: Post-reform Period



The estimates point to a program preference for non-locals. Odense tends to prefer students from Aarhus or other regions over Odense locals and Aarhus tends to prefer students from Odense or elsewhere over Aarhus locals. This points to program preference over student diversity, based on region of origin. Potentially consistent with this, we see that the non-graduation preferences at Aarhus are decreasing in student gpa, giving low gpa student an edge in admissions. This is not true for students from Aarhus applying to Odense. Here, we find the largest the non-graduation preferences for students in higher gpa groups.

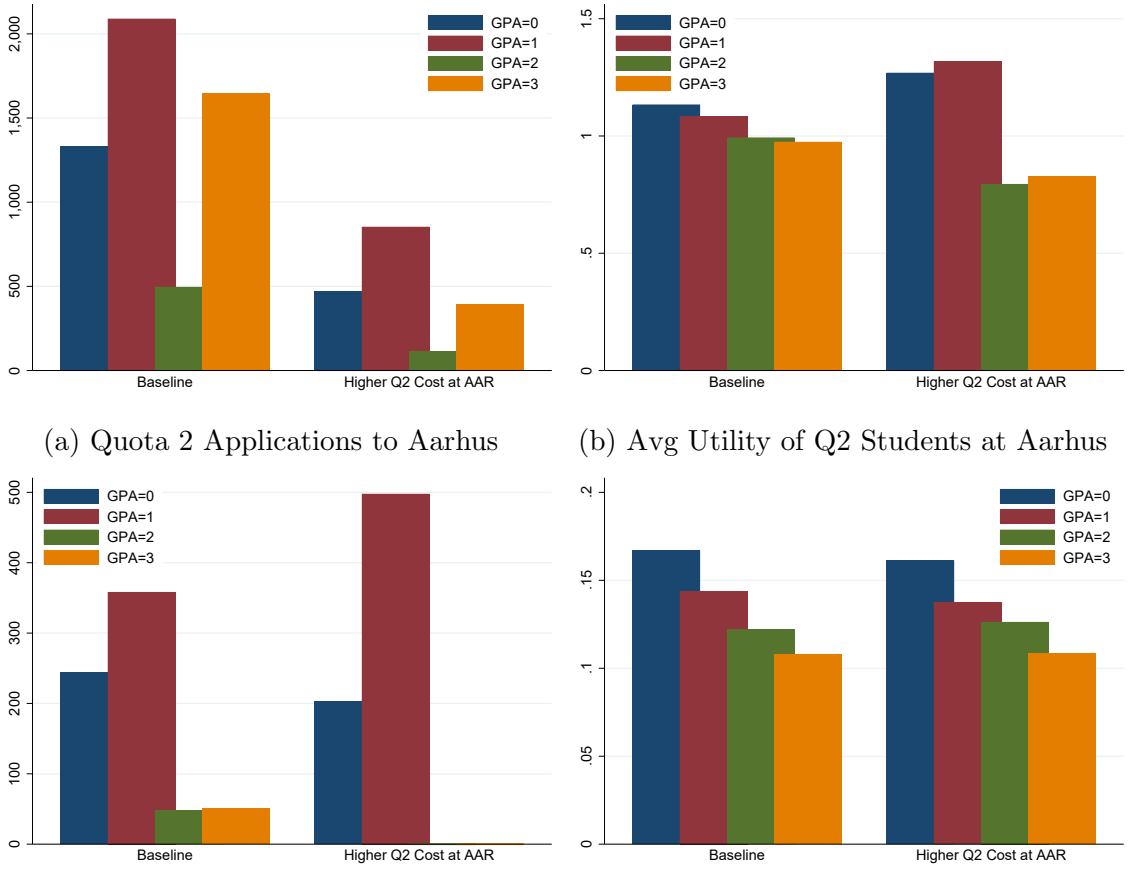
8 Counterfactuals

Our empirical evidence suggests that the admission reform led to an increase in persistence at Odense. Building on this evidence we next investigate whether Aarhus could copy the Odense admission reform model and thereby increase their own graduation rates. Specifically,

we separately investigate the effects of changes in application costs and the improvement in signal quality, before changing them jointly. Throughout our counterfactual analysis, we focus on the post-reform period.

Increasing Quota 2 Application Costs: We first investigate the effects of changes in quota 2 application costs in isolation. To this end, we increase Aarhus mean quota 2 application costs from 0.8 to Odense's mean cost of 2.3, see panel I in Table 7. Figure 7 summarizes the effects on applications, enrollment, utility, and graduation at Aarhus by gpa in the first two panels of each figure.

Figure 7: Increasing Quota 2 Application Costs at Aarhus



(a) Quota 2 Applications to Aarhus

(b) Avg Utility of Q2 Students at Aarhus

(c) Quota 2 Enrollment at Aarhus

(d) Quota 2 Dropout at Aarhus

Starting with Figure 7a, we see that increasing quota 2 application costs reduces the number of applications to Aarhus, especially among high gpa students who have a high probability of quota 1 admission. Since the remaining Q2 applicants with high gpa typically get into the program through quota 1, Aarhus is forced to admit more lower gpa candidates via quota 2 in order to fill their seats, see Figure 7c. This effect may lower overall persistence

Table 8: Counterfactuals: Changes and Application Costs and Signal at Aarhus

	Ode Completion	Aar Completion	# Doctors	Student Welfare
Baseline	0.913	0.864	0.892	0.385
Aar Q2 Costs Increase	0.914	0.875	0.897	0.362
Aar Q2 Signal Improves	0.912	0.911	0.912	0.386
Aar Q2 Signal and App cost Up	0.913	0.891	0.904	0.358

Note: This table summarizes the counterfactual effects of changes in Aarhus' signal precision as well as Aarhus quota 2 application costs. The first and second column present the average persistence rate among quota 2 students at Odense and Aarhus, respectively. The third column presents the overall share of graduating doctors among students admitted via quota 2. The fourth column presents student welfare denoted in utility units, taking quota 2 application costs into account. The first row summarizes the post-reform equilibrium. The second row summarizes outcomes after increasing Aarhus quota 2 application costs to Odense's post-reform quota 2 application costs. The third row summarizes outcomes after increasing Aarhus signal precision to Odense's post-reform signal precision. Finally, the last row summarizes outcomes after increasing Aarhus Aarhus signal precision and quota 2 application costs jointly.

rate at Aarhus as lower gpa students have lower completion rates on average, see the baseline estimates in Figure 7d. Yet, the increase in application costs also leads to an advantageous selection in student preferences among lower gpa students (gpa=0 and gpa=1) as indicated by Figure 7c.[22] Since preferences are positively correlated with talents, see again panel I in Table 7, this leads to an increase in persistence among lower gpa students as evidenced in Figure 7d.

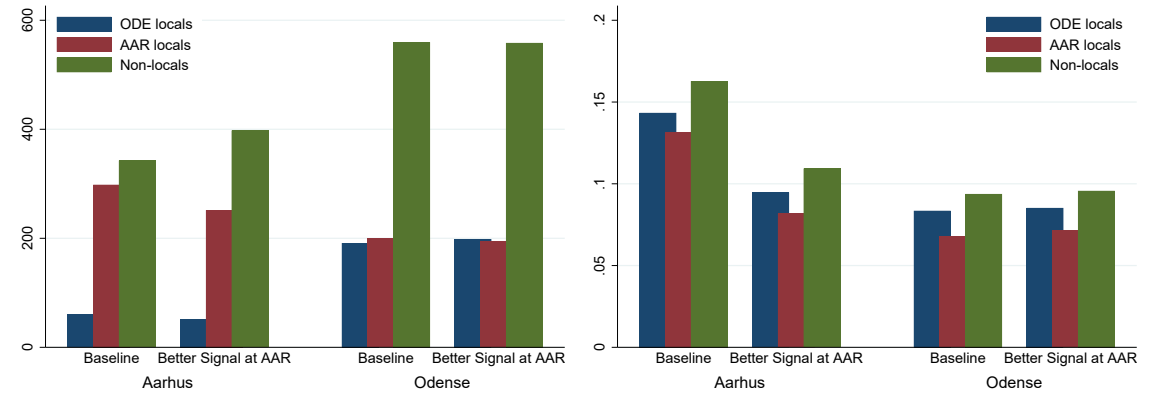
On net, we find a small increase in completion rates at Aarhus as indicated in Table 8. Focusing on the second column, we see an increase in Aarhus completion rate by 1.1 p.p. as we increase in quota 2 application costs. We find only minimal spillover effects on completion rates at Odense, see the first column. Overall, we see a very small increase in the overall number of graduating doctors per quota 2 seat across programs of 0.2 p.p, see column 3. At the same time we see a decline in student utility, suggesting that the increase in application costs outweighs better matching on preferences.

Increasing Quota 2 Signal Precision: Next, we turn to Aarhus signal precision. In this counterfactual we only increase Aarhus post-reform signal precision from 0 to 0.19, which corresponds to Odense's signal precision in the post-reform period, see again panel I in Table 7. Figure 8 summarizes the effects on enrollment, and graduation at Aarhus and Odense by student location in panels 1 and 3 of each figure.

Starting with Figure 8a, we see that as the signal precision at Aarhus increases, Aarhus admits fewer local students, which is consistent with a reduction in the winner's curse. Similarly, we see a (very small) increase in the number of local students admitted to Odense,

[22]Selection does not improve among high gpa students because the remaining Q2 applicants in this group are mainly selected on very low application cost draws rather than high utility.

Figure 8: Increasing Quota 2 Signal Precision at Aarhus



(a) Quota 2 Enrollment

(b) Quota 2 Dropout

along with a small decline in the number of admitted Aarhus locals, which is consistent with a worsening of the winner's curse at Odense. Overall, we see a large increase in persistence (decline in dropouts) at Aarhus in Figure 8b, but almost no spillover in graduation rates at Odense. Quantitatively, the completion rate increases by 4.7 p.p. at Aarhus leading to an overall increase across programs of 2 p.p. see columns 2 and 3 of Table 8. Completion rates at Odense as well as student utility remain largely unchanged. This suggests that improved signal precision may yield limited negative spillovers if the rival program can mitigate the winner's curse through their own screening.

Finally, we consider changing signal precision and application costs jointly. The effects are summarized in the last row of Table 8. We find an increase in completion rates at Aarhus and overall, but the effect sizes are smaller than the estimates from the third, which held the application costs fixed. These results suggest that improved signal precision is less effective when the applicant pool is decimated because of high application costs.

9 Discussion and Next Steps

Our model estimates confirm the presence of interdependent program values and student self-selection. The relative importance of these channels will play an important role for the welfare effects of different policy counterfactuals. Our findings suggest that Odense's signal precision increased after the reform, potentially worsening the winner's curse at Aarhus. The strong correlation between student preferences and talents provides a micro foundation as to why the additional screening efforts as part of Odense's reform intend to reveal student knowledge but also and importantly motivation, that may be strongly correlated with preferences. Our findings also suggest that part of Odense's success in lowering dropouts rates

can be attributed to an increase in application costs, which deterred students with weaker preferences, who have higher dropout rates on average, from applying to Odense in the first place. Put differently, quota 2 application costs provide an instrument for market signalling in the spirit of Spence (1973). At the same time, preferences are correlated between programs and higher application costs may also discourage talented students from applying who view the rival program as a close substitute. As the counterfactual analysis for Aarhus shows, a smaller talent pool can substantially limit the benefits from higher signal precision. Therefore, Odense's strategy to combine their intensified screening with an expansion of quota 2 seats can be seen as a direct attempt to mitigate this problem by raising admission chances and hence incentives for promising students to apply.

While the counterfactuals so far have illustrated potential gains from better screening at the rival program with limited spillovers, the results also raise questions about further improvements through changes in the information structure. For example, the current analysis has ignored the costs of screening for each individual program, and a centralized review process with information sharing across programs could be an attractive alternative.

To answer these questions, we plan to use the estimated model to simulate the following experiments:

1. **Common Program Signals:** To assess the role of interdependent program values, we intend to simulate counterfactual admission and quota 2 application decisions, when programs observe the own and the rival signal.

2. **Observed Preference shocks:** To assess the role of self-selection, we intend to simulate counterfactual admission and quota 2 application decisions, when programs observe the students' preference shocks.

3. **Preference Signalling:** To internalize the information provided through costly quota 2 applications more effectively, we consider a counterfactual in which programs observe whether students applied to the rival program via quota 2. This may provide useful information to Aarhus in the post-reform period but may also give student an incentive to apply at Odense to increase their admission chances at Odense **and** Aarhus.

4. **Early Admissions:** Building on these results, we intend the simulate the effects of a decentral assignment mechanism that allows for early admissions. One possibility would be that students are allowed to apply to at most one program via quota 2. This may be interpreted as an 'early action' admission program (used by some U.S. schools) where students are accepted early but are not committed to enroll. In our setting,

students can still apply to other programs via quota 1 and accept those offers if they prefer them.

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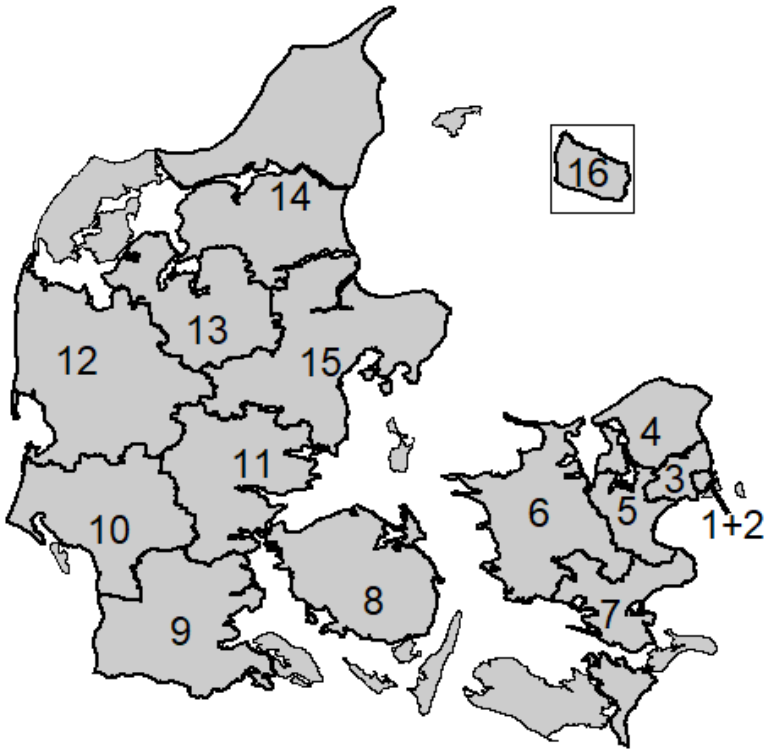
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Appendix

A Data and Institutions

A.1 Danish Geography

Figure 9: Counties of Denmark



	Description	Abbreviation	Our Location Code
1+2	Copenhagen and Frederiksberg Municipalities	CPH-FR Munic	0
3	Copenhagen County	KH	0
4	Frederiksborg County	FR	0
5	Roskilde County	RS	0
6	West Zealand County	VS	1
7	Storstrom County	ST	1
8	Funen County	FY	1
9	South Jutland County	SJ	1
10	Ribe County	RB	0
11	Vejle County	VJ	2
12	Ringkjobing County	RK	0
13	Viborg County	VB	2
14	North Jutland County	NJ	2
15	Aarhus County	AR	2
16	Bornholm	BO	0

A.2 Timeline of Reforms

Application to higher education in Denmark with a particular focus on Medicine All years denote the year in which the application procedure may be affected.

- 1994: We have application data from 1993 onwards. The 1993 cohort is of relatively poorer quality, usually we use 1994 as start year.
- 1999: Change in the Higher Education Act: Universities are no longer free to set the Q2 share. The aim is to reduce the share of Q2 students to 20-25 pct.
- 2002-2007: SDU Health is exempted from the Q2 rule, and increase Q2 share to almost 50 pct. while intensifying the screening process.
- 2006: Bonus A is introduced: students multiply their GPA with 1.03 for one and 1.06 for two extra A level high school course.
- 2007: A new grade scale is introduced collapsing the ten previous individual grades to seven broader categories. GPAs obtained from graduation before 2007 is converted via a fixed table (see first page: https://bit.ly/32v81mE).
- 2008: The Q2 share is limited to 10 pct. Subject-specific prerequisites are aligned across universities and faculties. The prerequisites for medicine are already aligned across universities, but course requirements are increased substantially. SDU Health introduces the formalised UNI-test as part of the Q2 admission process
- 2009: Grade bonus for applying within 2 years of high school graduation is introduced. The GPAs of applicants applying through Q1 in the first coming two application processes after high school graduation are multiplied by 1.08. The first high school cohort affected is the 2007 cohort. Extensions are granted for military service. Cancelled in 2020. The course requirements for Bachelor's programs in general are loosened, medicine is not affected. The conditions for earning extra "turbo" credits during the summer is improved (conditional admission). The age priority for admitting same GPA applicants with limited seating is ruled illegal and all students on the GPA threshold are admitted via lotteries. All medicine programs are expanded: KU and SDU with approx. 50 students. AU with approx. 100 students
- 2010: Aalborg University (AAU) opens a medicine program with 57 seats. KU is reduced with 50 students again. SDU is reduced with 10 seats and AU is increased with 10 seats.

- 2012: The Q2 share is set free (subject to approval from the minister). In effect, this change applies to the applicant and onwards as the rules were changed a mere eight days before the programs had to announce Q1/Q2 seats available for applicants. Still, many programs continue with 10 pct. Q2 seats.

- 2014: The extensive Fremdriftsreformen (the progress reform) is introduced to reduce the time until labor market entry (Danish students on average complete their Master's degree in 6.1 years—the norm is 5 years). Students are required to be enrolled full time (60 ECTS per year) and are automatically signed up for exams and reexams. The SU grant is removed if a student falls too far behind. The student earns a bonus for completing before time.

- 2015: Last cohort of application data on project 4937. Aalborg University (AAU) increase their medicine program with 50 seats to 110. Aarhus University (AU) pilot test Multiple-Mini-Interviews as an intensified screen process in medicine.

- 2016: Aarhus University (AU) increase their medicine Q2 share from 10 to 20 pct. and introduce Multiple-Mini-Interviews in addition to a multiple choice admission test. The MMI's are dropped in 2018.

B Theory

Proof of Proposition 1

The following (standard) lemma is used in our argument.

Lemma 1 *Let (c,d) be an interval on the real line. Suppose $J(\theta)$ is non-decreasing and $H(\theta)$ is quasi-monotone, i.e. crosses zero once, from below. Suppose, for some measure μ on $\mathbb{R}$, we have*

$$\int_c^d H(v)d\mu(v) = 0.$$

Then

$$\int_c^d H(v)J(v)d\mu(v) \geq 0.$$

Proof. Because $H(\cdot)$ is quasi-monotone and integrates to zero, there exists some $v_0 \in (c,d)$ such that $H(v) \geq (\leq)0$ for $v > (<)v_0$. Then

$$\begin{aligned}\int_c^d H(v)J(v)d\mu(v) &= \int_c^d H(v)(J(v)-J(v_0))d\mu(v)\\ &= \underbrace{\int_c^{v_0} H(v)(J(v)-J(v_0))d\mu(v)}_{\geq 0} + \underbrace{\int_{v_0}^d H(v)(J(v)-J(v_0))d\mu(v)}_{\geq 0}.\end{aligned}$$

The inequality is strict when $H(\theta) \neq 0$ for $\theta \neq v_0$ and $J(\theta)$ is strictly increasing. ■

We now fix $j \in \{1,2\}$, fix strategies (ℓ, a, r) and associated cutoffs $\underline{r}$, and consider two signal values, $s_j' > s_j$. It will suffice to show that $E(\omega_j|s_j', D_j^2(x) > E(\omega_j|s_j, D_j^2(x)$, where we omit D_j^2's dependence on $(\underline{r}, \ell, a, r)$ for brevity. We have

$$\begin{aligned}E(\omega_j|s_j, D_j(x)) &= \int \omega_j f(\omega_j|s_j, D_j(x))d\omega_j\\ &= \int \omega_j \frac{f(s_j|\omega_j, D_j(x))}{f(s_j|D_j(x))} f(\omega_j|D_j(x))d\omega_j\\ &= \int \omega_j \frac{f(s_j|\omega_j)}{f(s_j|D_j(x))} f(\omega_j|D_j(x))d\omega_j,\end{aligned}$$

where the final line follows by Assumption 2. Hence it suffices to show

$$\int \omega_j \left(\frac{f(s_j'|\omega_j)}{f(s_j'|D_j(x))} - \frac{f(s_j|\omega_j)}{f(s_j|D_j(x))}\right) f(\omega_j|D_j(x))d\omega_j > 0. \tag{23}$$

Observe that

$$\int f(\omega_j|s'_j, D_j(x))d\omega_j = \int f(\omega_j|s_j, D_j(x))d\omega_j = 1,$$

and hence

$$\int \left(\frac{f(s'_j|\omega_j)}{f(s'_j|D_j(x))} - \frac{f(s_j|\omega_j)}{f(s_j|D_j(x))} \right) f(\omega_j|D_j(x))d\omega_j = 0.$$

Consider the term $\left(\frac{f(s'_j|\omega_j)}{f(s'_j|D_j(x))} - \frac{f(s_j|\omega_j)}{f(s_j|D_j(x))} \right)$. Rearranging, we may rewrite it as

$$\left(\frac{1}{f(s'_j|D_j(x))} \left(\frac{f(s'_j|\omega_j)}{f(s_j|\omega_j)} \right) - \frac{1}{f(s_j|D_j(x))} \right) f(s_j|\omega_j).$$

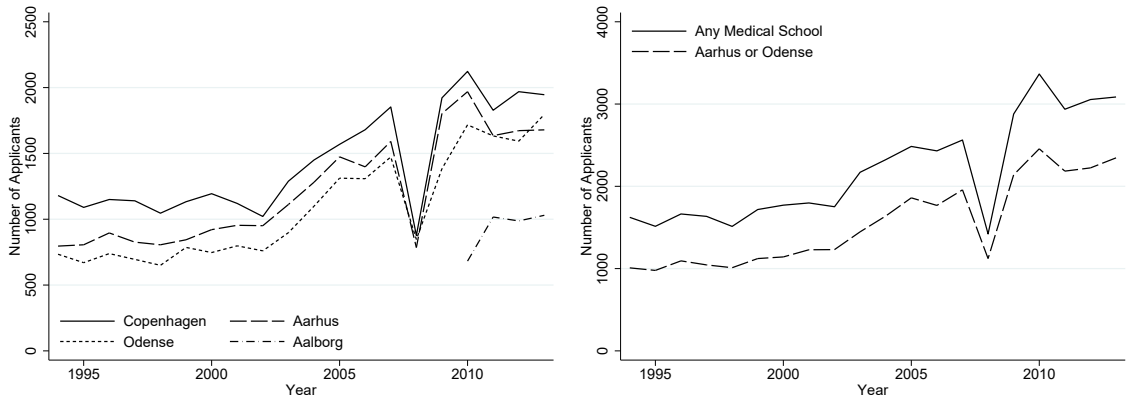
By Assumption 3, the term in parentheses is monotone increasing in ω_j, negative for sufficiently small ω_j, and positive for sufficiently large ω_j. The term $f(s_j|\omega_j)$ is a density and is (by assumption) always positive. Hence this expression crosses zero once from below as a function of ω_j.

By Lemma 1, it follows that equation 23 is satisfied.

C Additional Empirical Results

C.1 Details on Applicants

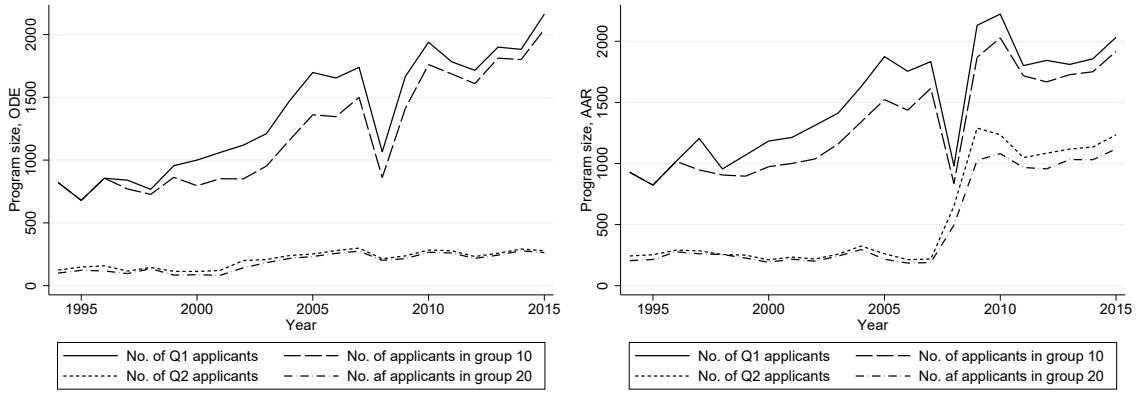
Figure 10: Applicants and Applications



(a) Number of Applications by Program (b) Number of Unique Applicants

Note: Figure 10a shows the annual number of applicants who list each medical school among their up to 8 priorities. Since applicants can list multiple medical schools in their preferences, Figure 10b reports the total number of unique applicants who apply to at least one Danish medical school or at least one of the two focal programs in Aarhus and Odense over time.

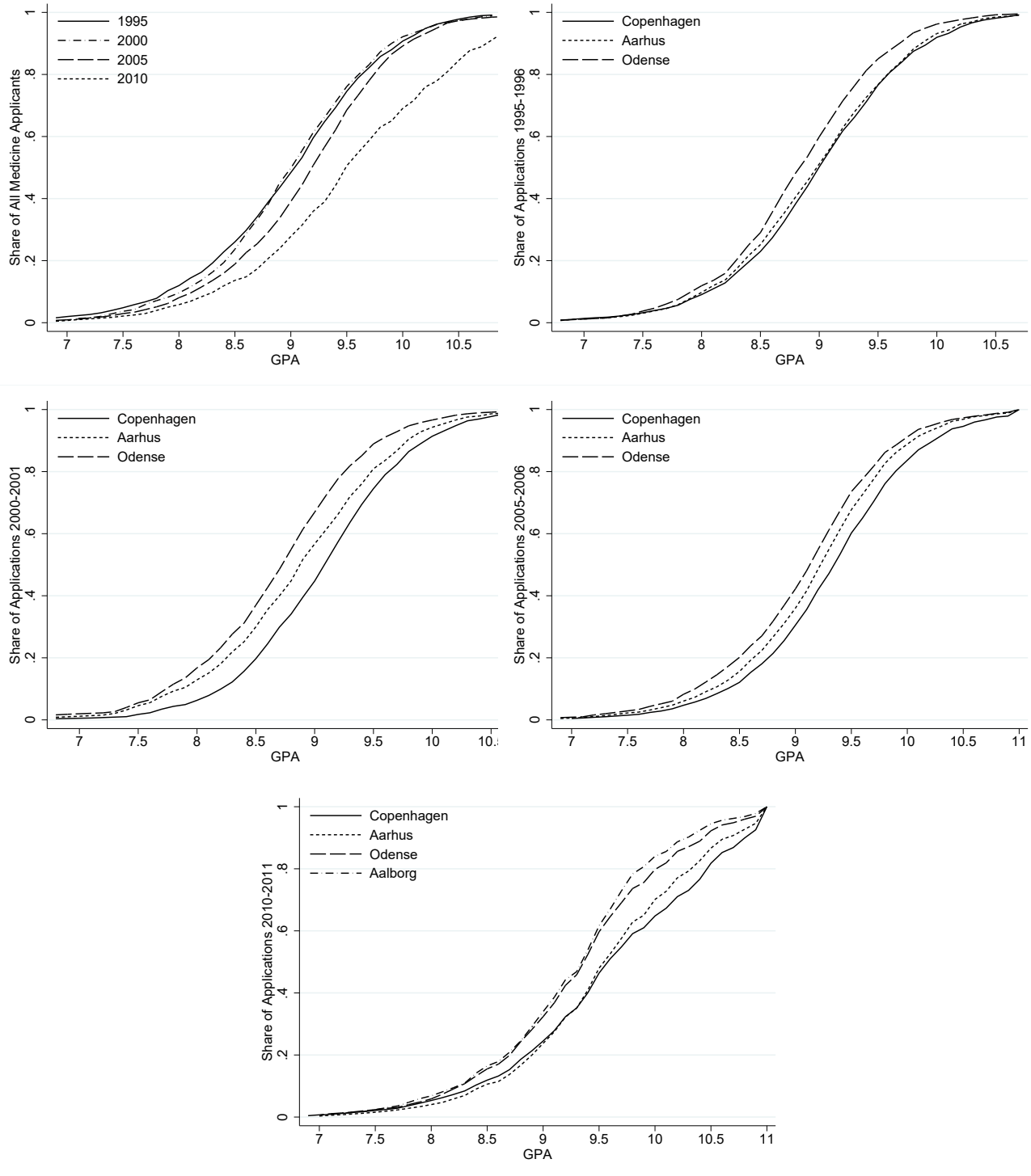
Figure 11: Applicants by Application Type



(a) Applicants by Quota and Group, Odense (b) Applicants by Quota and Group, Aarhus

Note: Figures 11a and 11b show the annual number of applicants to Quota 1 and 2 in Aarhus and Odense, respectively. Our sample includes all applicants through groups 10 and 20, which represent the vast majority of applicants in each quota.

Figure 12: GPA Distribution of Medical School Applicants

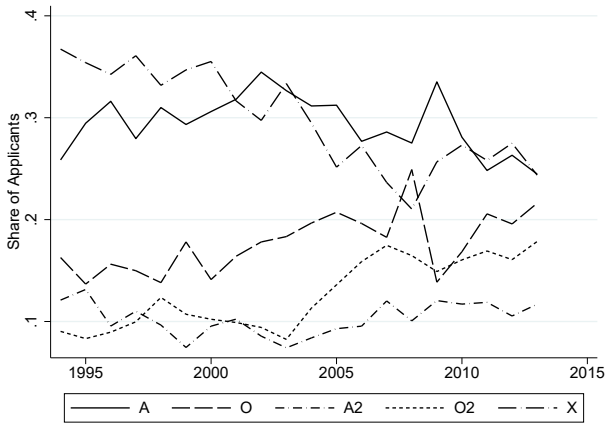


Note: The figure presents the high school GPA distribution for four different applicant groups, pooling two cohorts each. Each cohort includes applicants who indicate at least one of the four medical school programs in their submitted preference ranking. GPA is harmonized to the 7-point scale in all years.

Applicant Preferences Figure 1a presents evidence on student preferences, which organizes applicants in four distinct regions of residence: counties close to Odense, counties close to Aarhus, all other counties in Denmark, and foreign applicants.[23] Within each region, we display the share of applicants by five preference types. Here, "A" denotes that an applicant's first priority among medical programs is Aarhus, and "O" denotes top priority for Odense. "A2" and "O2" denote preference rankings where an applicant lists a flagship program of either Copenhagen or Aalborg first, and Aarhus (A2) or Odense (O2) second. "X" denotes cases where applicants do not list Aarhus or Odense as either first or second priority.

We note three insights from this figure. First, Copenhagen and Aalborg are most popular among applicants, but only in regions outside of Odense and Aarhus. Second, in counties close to Odense, Odense is the most popular program, whereas Aarhus is by far the most preferred program in counties close to Aarhus. In addition, Aarhus and Odense are often chosen as the second preferred option in the opposite region. Third, in all other Danish regions and among foreign applicants, there is no clear preference order between Aarhus and Odense. More details on the preference ranking over time among applicants who apply to Odense or Aarhus is provided in Appendix Figures 13 and 14, respectively.

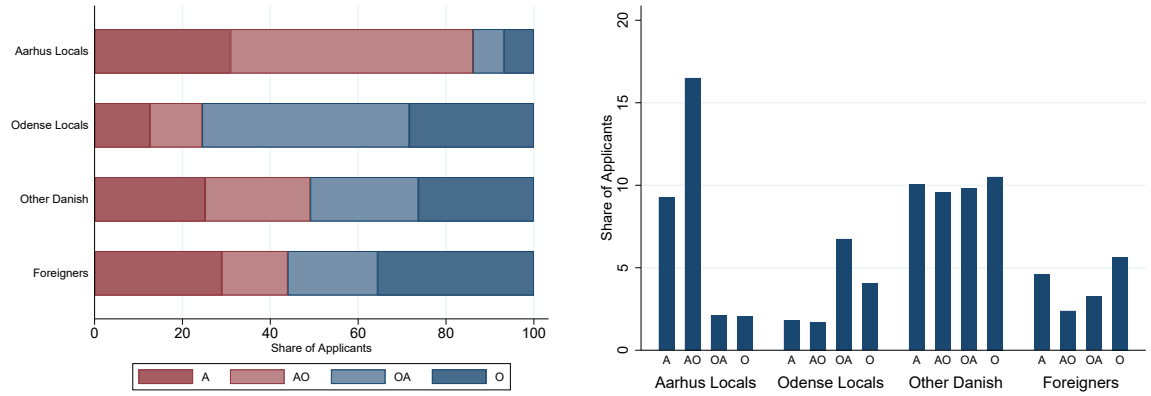
Figure 13: Program Preferences Over Time



Note: To simplify the exposition, we group all applications based on the two medical programs listed with highest priority, irrespective of whether the applicant lists a third medical program or not. A denotes Aarhus, and O denotes Odense, X summarizes Copenhagen and Aalborg (available from 2010 onward).

[23] Counties near Aarhus include North Jutland, Aarhus, Vejle, Viborg, while counties near Odense include Funen, Storstrom, West Zealand, and South Jutland, see Appendix Figure 9 for a map. Figure 13 presents trends in the relative popularity of Aarhus and Odense over time.

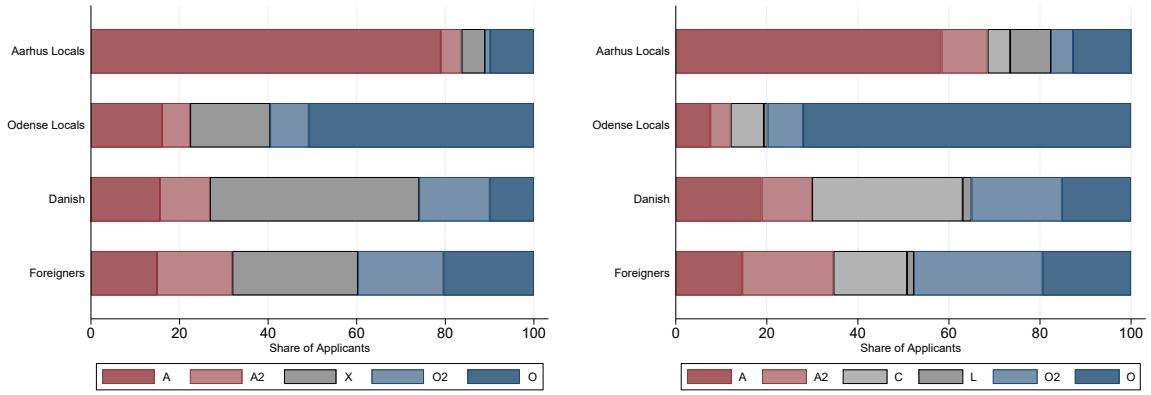
Figure 14: Preferences over Aarhus versus Odense by Applicants' Residence



(a) Distribution of Relative Rankings (b) Frequency of Relative Rankings

Note: These figures only include applicants who list at least one of the medical programs in Aarhus and Odense among their priorities. The different preference orders we report are "A" for applicants who only list Aarhus but not Odense, "AO" for applicants who assign a higher priority to Aarhus than Odense, and vice versa for "OA" and "O". Odense (Aarhus) locals refer to residents of counties with location code "1" ("2"), while Danish denotes all other areas of Denmark with location code "0", see Figure 9.

Figure 15: Preferences over Aarhus versus Odense by Applicants' Residence



(a) Distribution of Relative Rankings (b) Frequency of Relative Rankings

Note: These figures only include applicants who list at least one of the medical programs among their priorities. Figure 15a shows applicant preferences for cohorts 1994–2009, while Figure 15a shows the patterns for 2010–2013, the period when Aalborg is available as a fourth medical program. The different preference orders are denoted by "A" for applicants who list Aarhus first, "A2" for applicants who prefer Copenhagen or Aalborg to Aarhus, and similarly for "O" and "O2" among applicants to Odense. Applicants who only apply to Copenhagen or Aalborg are denoted "C" or "L" respectively.

C.2 Details on Admissions

Table 9: Odense and Other Medical School Programs

University	Program	% applying to j	% applying to j below	% applying to j next	% admitted to j	% applying to Odense	% rejected at Odense
Copenhagen	Biology	1.8%	1.5%	0.4%	0.7%	5.2%	1.9%
Copenhagen	Psychology	1.8%	1.4%	0.5%	0.0%	2.0%	0.0%
Aarhus	Psychology	1.9%	1.5%	0.3%	0.1%	3.0%	0.2%
Odense	Biomechanics	4.4%	3.2%	1.3%	1.4%	41.0%	15.8%
Aarhus	Dentistry	7.4%	5.4%	1.1%	0.7%	28.0%	5.5%
Copenhagen	Dentistry	8.4%	6.1%	2.1%	1.0%	23.3%	6.1%
Aalborg	Medical School	12%	8.8%	3.7%	0.2%	77.2%	11.1%
Copenhagen	Medical School	67.6%	19.1%	12.9%	0.7%	47.8%	0.8%
Aarhus	Medical School	70.1%	31.7%	25.1%	2.7%	62.8%	4.3%
Odense	Medical School	100.0%	0.0%	0.0%	0.0%	100.0%	0.0%
Sample		Applicants to Odense	Applicants to Odense	Applicants to Odense	Rejected at Odense	Applicants to Program j	Admitted to Program j

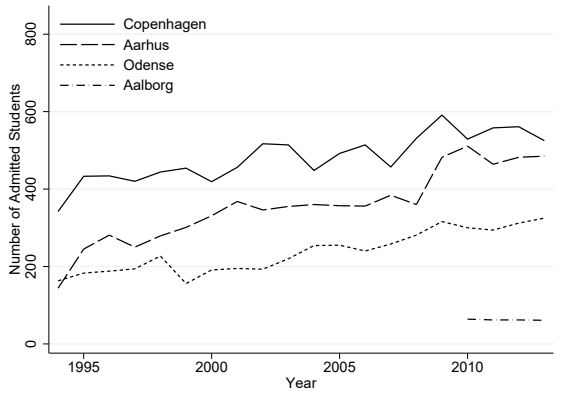
Note: This table presents summary statistics for applicants that apply to Odense's medical program. For cells with low case numbers we censor the share of the sample to zero to preserve confidentiality.

Capacity Figure 16a describes the number of admissions by program and year. Overall, admissions are quite stable over time, with a modest expansion across all existing programs in 2009: Copenhagen and Odense increased their capacity by 50 seats, while Aarhus expanded by 100 seats, see Section A.2 for further details. Aalborg opened a small medicine program with less than 100 seats in 2010. At the same time, the number of applicants per year that apply to at least one medical program in Denmark gradually increased from 2,200 in the late 1990s to 3,300 after 2010, see Appendix Figure 10.

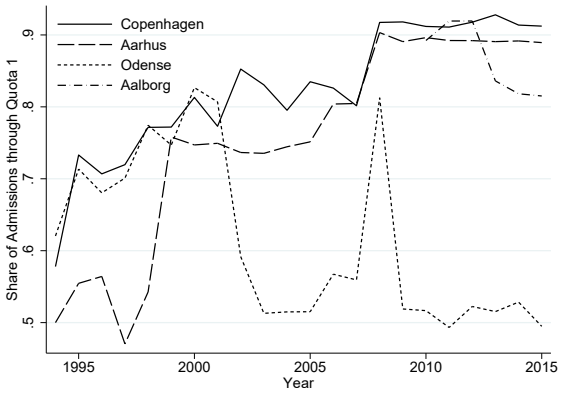
Quota 1 Admissions Figure 16b documents the share of quota 1 admissions out of all admissions by program and year. Figure 16e documents the quota 1 GPA cutoff, which is inversely related to the quota 1 share, holding the applicant pool fixed. To put the magnitude of the GPA cutoff into perspective, we present the distribution of high school GPA among medical school applicants in Appendix Figure 12.[24] The quota 1 share varied considerably between programs in the mid 1990s until a 1999 change to the Higher Education Act required that programs were no longer free to determine their quota 1 share. The goal of this reform

[24]The GPA scale changed from a 13-point to a 7-point scale in 2007. We use a crosswalk to translate all years into a unifying scale, see shorturl.at/vHOR6 last accessed Jan 25, 2020.

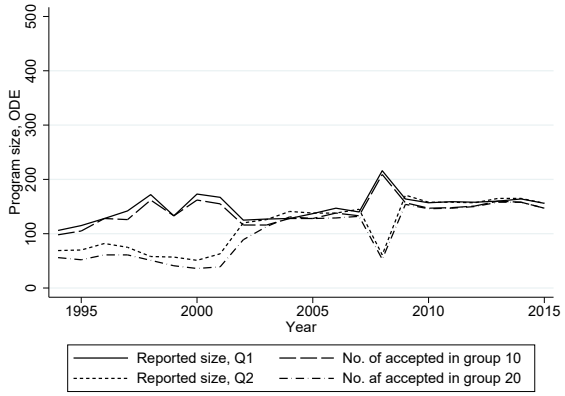
Figure 16: Admissions to Medical School Programs 1994-2013



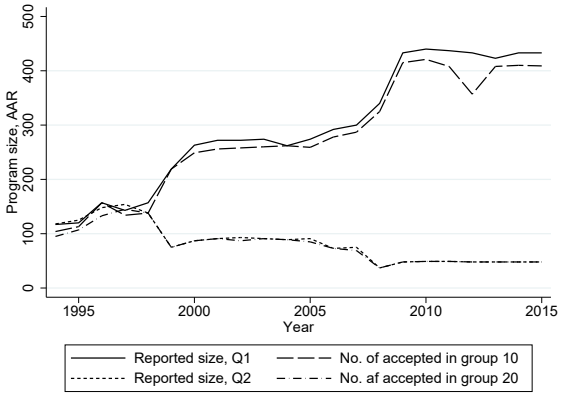
(a) Admissions to Medicine Programs



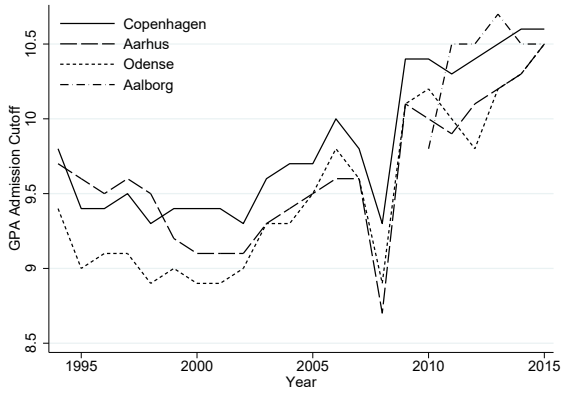
(b) Quota 1 Admission Share



(c) Program Size, Odense



(d) Program Size, Aarhus



(e) GPA Cutoff for Regular Admission

Notes: Data come from the Danish Central Admissions Secretariat (CAS). Copenhagen and Odense increased their capacity by 50 seats in 2009, whereas Aarhus increased their capacity by 100 seats in 2009, see Figure 16a. Figure 16b documents the share of quota 1 admissions out of all admissions by program and year. Figures 16c and 16d show the annual number of seats in Quota 1 and 2 in Aarhus and Odense, respectively. Our sample includes all applicants accepted through groups 10 and 20, which represent the vast majority of admitted students in each quota. Figure 16e documents the quota 1 GPA cutoff by program over time, using a harmonized 7-point grading scale for all years.

was to standardize the quota 2 share to 20-25 percent, explaining the convergence in the quota 1 share, predominantly affecting Aarhus, which had the smallest quota 1 share prior to this reform. While Aarhus started out with the highest GPA threshold in the mid 1990s, we observe a relative decline in their GPA cutoff starting in 1999, consistent with the increase in Aarhus' quota 1 share in response to the reform.

As a consequence, GPA thresholds in Aarhus and Odense have tracked each other very closely since the early 2000s, while Copenhagen had a substantially higher GPA admission threshold than all other programs from 2000 onwards. Similar to the 1999 reform, the regulated quota 1 share was further increased to 90 percent in 2008, reconciling the increase in Figure 16b for Copenhagen and Aarhus. While the reform may have contributed to a decline in the GPA cutoff, we believe that the drastic reduction in 2008 was primarily driven by a substantial extension to the course pre-requisites for medicine programs, which was also introduced in 2008 and led to a decline in the number of applications. Importantly, the extension was lifted again in 2009, reconciling the immediate increase in the GPA cutoffs.

C.2.1 Quota 1 and Quota 2 Admissions

Figure 17 complements the evidence in Figure 2 and Table 2. The evidence in the left panel shows the discontinuity in admission chances at the GPA threshold. In addition, Quota 2 admission chances increase substantially with GPA at Aarhus, but are constant across a wide GPA range at Odense and Copenhagen. Programs further differ in the level probability of Quota 2 admissions. The right panel of Figure 17 shows the discontinuity in dropout rates at the GPA threshold separately by program. Interestingly, dropout rates are constant across students with different GPA admitted through Quota 2 at Odense, whereas dropout rates increase steeply for low GPA students admitted via Quota 2 at Aarhus.

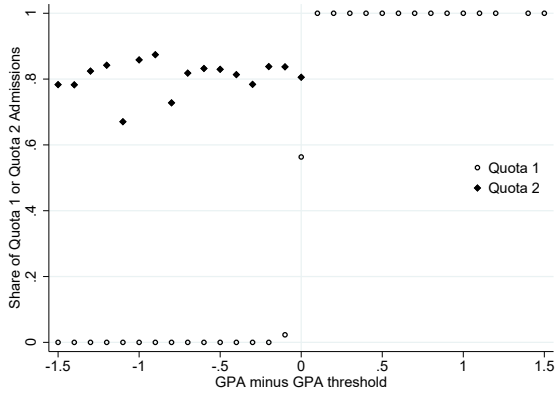
To determine the value of screening more formally, we estimate regression-discontinuity models,

$$\begin{aligned} Y_{ijt} &= \gamma_0 + \gamma_{gpa_{q1}} \cdot gpa_i \cdot \mathbb{1}\{GPA \geq cutoff\} + \gamma_{gpa_{q2}} \cdot gpa_i \cdot \mathbb{1}\{GPA < cutoff\} \\ &+ \gamma_s \cdot \mathbb{1}\{GPA < cutoff\} + \gamma_{jt} + \epsilon_{ijt}, \end{aligned} \tag{24}$$

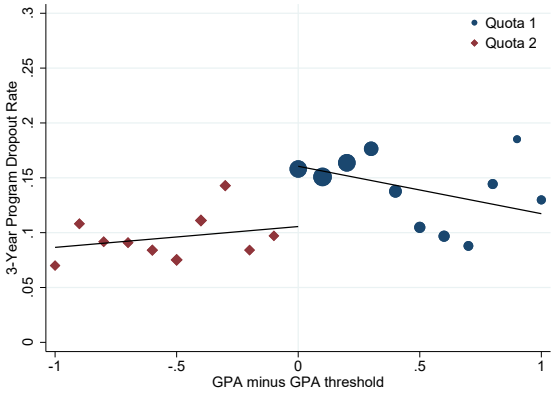
where we control for differential linear trends in gpa to the left and right of the GPA cutoff. The key parameter of interest is γ_s, which denotes the discontinuous change in the outcome measure when going from quota 1 to quota 2. Graphically, this corresponds to going from the right of the cutoff to the left of the cutoff in Figure 2b.

We revisit the main findings from Table 2 in various robustness exercises, which we summarize in Appendix Tables 10 and 11. We show that the discontinuity is robust to using the 1-year dropout rate or overall completion rates for cohorts 1994–2009 as alternative

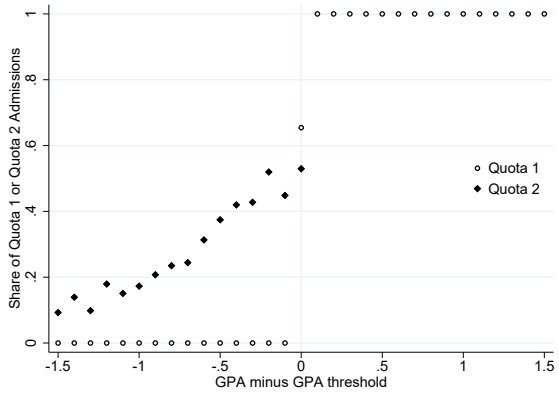
Figure 17: Admissions and Dropouts by Quota



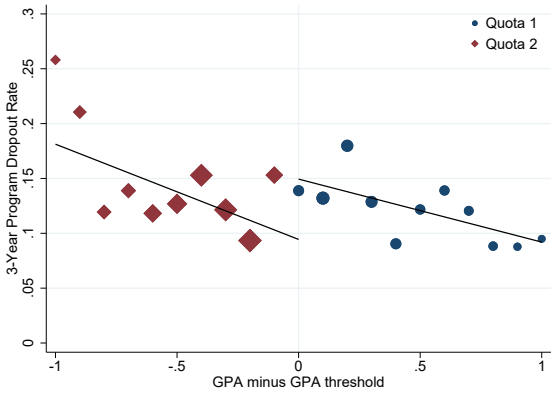
(a) Admissions by GPA: Odense



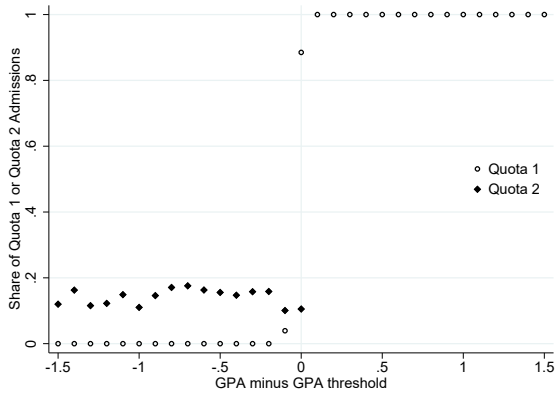
(b) Dropouts by GPA: Odense



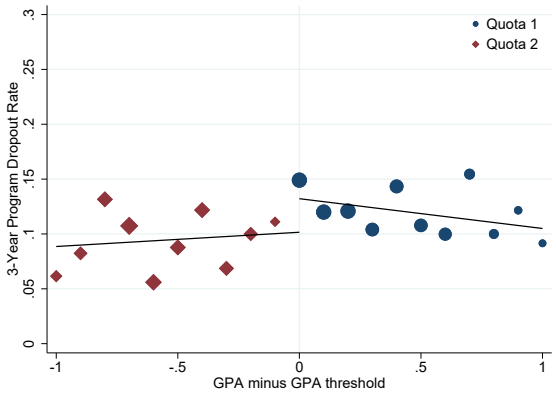
(c) Admissions by GPA: Aarhus



(d) Dropouts by GPA: Aarhus



(e) Admissions by GPA: Copenhagen



(f) Dropouts by GPA: Copenhagen

Note: Figures 17a, 17c, and 17e plot the fraction of admitted applicants to Odense, Aarhus, and Copenhagen by quota on the vertical axis. On the horizontal axis, we measure the difference between the student's GPA and the program's GPA cutoff in grade-points. Figures 17b, 17d, and 2b maintain the same horizontal axis but plot the 3-year dropout rate on the vertical axis for students in each program, respectively. This figure omits students admitted via quota 1 (quota 2) whose GPA is below (above) the GPA cutoff. The lines denote the best linear fit of dropouts on GPA among quota 1 and quota 2 enrollees, weighted by the number of observations in each bin.

Table 10: Programs' Information Quality and Student Persistence

	(1) 1Y Dropout	(2) 1Y Med Dropout	(3) Completion	(4) Time to Complete
γ_s	-0.030***	-0.026***	0.071***	-43.842**
	(0.009)	(0.009)	(0.016)	(17.545)
$\gamma_{gpa_{q1}}$	-0.000	-0.000	0.004***	-1.837
	(0.001)	(0.001)	(0.001)	(1.552)
$\gamma_{gpa_{q2}}$	-0.001	-0.000	0.006**	-5.148*
	(0.001)	(0.001)	(0.003)	(2.890)
Constant	0.112***	0.082***	0.783***	2,745.920***
	(0.019)	(0.019)	(0.031)	(35.770)
Observations	15,554	15,554	11,476	9,633
R-squared	0.009	0.008	0.011	0.088

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Note: This table presents estimates from regression model (2). The first row presents $\gamma_{screening}$, rows 2 and 3 present $\gamma_{gpa_{q1}}$ and $\gamma_{gpa_{q2}}$. Column 1 considers the one-year dropout rate at any enrolled program among admitted students to Aarhus or Odense. Column 2 exclude transfers into other medical programs in measuring one-year dropouts. Column 3 and 4 analyze completion rate and time until completion among graduates, respectively. All columns pool enrolled students at both institutions.

outcome measures. The difference in 1-year dropout rates at the GPA threshold equals 3 percentage points, and we find 7.1 percentage points differences in total completion. In addition, column 4 of Table 10 shows that students admitted through Quota 2 take less time (44 days) to complete their studies on average.

Finally, we find qualitatively similar results when focusing on the 40 percent of students who applied through quota 2, some of them were still admitted through quota 1, see Table 11. These students may be more motivated on average, as they are willing to engage in a more tedious and costly quota 2 application process. At the same time, we loose several applicants who are confident to be admitted via quota 1 and hence do not see the necessity to apply through quota 2 as well. Here, and as expected, the effects are noisier than for quota 1 admissions. The linear fit points to a 2.7 percentage points discontinuity for 3-year dropout rates at the GPA threshold. This difference increases to 5.3 percentage points and is more precisely estimated for total completion rates.

C.2.2 Program Ranking and Dropout Outcomes

In this subsection, we provide additional evidence on screening efforts and dropout outcomes of quota 2 applicants to Copenhagen, Aarhus, and Odense medical programs.

Table 12 complements Figure 3 and estimates more formally the differences in dropout rates among enrolled students at each program according to their position on the program's ranking for admissions. As in Figure **??**, we rank students admitted through Quota 2 from -1 for the highest-ranked student to 0 for the lowest, while Quota 1 admissions are ranked from 0 for the student with lowest GPA to 1 for the highest.

To compare marginal students admitted through Quota 1 and Quota 2 more formally,

Table 11: Programs' Information Quality and Student Persistence among Quota 2 Applicants

VARIABLES	(1) 1Y Dropout	(2) 1Y Med Dropout	(3) 3Y Dropout	(4) 3Y Med Dropout	(5) Completion	(6) Time to Complete
γ_s	-0.019*	-0.015	-0.027*	-0.020	0.053***	-27.957
	(0.010)	(0.010)	(0.016)	(0.015)	(0.020)	(21.877)
$\gamma_{gpa_{q1}}$	0.000	0.000	-0.001	-0.001	0.000	-7.607**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(3.786)
$\gamma_{gpa_{q2}}$	-0.000	-0.000	-0.002	-0.001	0.006**	-4.390
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(2.930)
Constant	0.069**	0.048*	0.189***	0.100**	0.786***	2,623.303***
	(0.027)	(0.026)	(0.043)	(0.041)	(0.049)	(55.336)
Observations	5,842	5,842	5,842	5,842	4,728	3,994
R-squared	0.011	0.011	0.016	0.014	0.018	0.119

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Note: This table presents estimates from regression model (2). The sample only includes students who have applied to their study program Aarhus or Odense via quota 2. The first row presents $\gamma_{screening}$, rows 2 and 3 present $\gamma_{gpa_{q1}}$ and $\gamma_{gpa_{q2}}$. Column 1 considers the one-year dropout rate and column 2 excludes transfers into other medical programs in measuring one-year dropouts. Columns 3 and 4 report analogous results for the 3-year dropout rate including or excluding transfers. Column 5 and 6 analyze completion rate and time until completion among graduates, respectively. All columns pool enrolled students at both institutions.

we estimate regression-discontinuity models,

$$\begin{aligned} Y_{ijt} &= \gamma_0 + \gamma_{perc_{q1}} \cdot (1 - perc_i) \cdot \mathbb{1}\{Q1adm\} + \gamma_{perc_{q2}} \cdot (perc_i - 1) \cdot \mathbb{1}\{Q2adm\} \\ &+ \gamma_s \cdot \mathbb{1}\{Q2adm\} + \gamma_{jt} + \epsilon_{ijt}, \end{aligned} \tag{25}$$

where $perc_i \in [0, 1]$ is the percentile rank of student i in their admission quota. We control for differential linear trends across the rankings for Quota 1 and Quota 2 students. The key parameter of interest is γ_s, which denotes the discontinuous change in the outcome measure when going from quota 1 to quota 2. Graphically, this corresponds to going from the right of the cutoff to the left of the cutoff at 0 in Figure **??**. Note that we rescale the percentiles such that the order is from best to worst among Quota 2 students, but from worst to best among Quota 1 students.

The pooled results in Table 12, column 1, show highly a significant increase in dropout rates for lower-ranked students in both quotas. Yet, there is no significant difference in dropout rates among marginal students from the two quotas. However, analyzing outcomes separately by program reveals substantial differences: While Copenhagen and Odense extract and act on dropout-relevant information in their Quota 2 rankings, as evidenced by a steep slope in dropout rates across the percentile ranking of Quota 2 students, we find zero correlation between the percentile ranking of Quota 2 students at Aarhus and their dropout rates. Finally, we document a 3.7 p.p. lower dropout rate among marginal Quota 2 students at Odense compared to marginal Quota 1 students, significant at 10% level, see column 3.

Table 12: Programs' Information Quality and Student Persistence

	(1) 1Y Dropout	(2) 1Y Med Dropout	(3) Completion	(4) Time to Complete
γ_s	-0.030***	-0.026***	0.071***	-43.842**
	(0.009)	(0.009)	(0.016)	(17.545)
$\gamma_{gpa_{q1}}$	-0.000	-0.000	0.004***	-1.837
	(0.001)	(0.001)	(0.001)	(1.552)
$\gamma_{gpa_{q2}}$	-0.001	-0.000	0.006**	-5.148*
	(0.001)	(0.001)	(0.003)	(2.890)
Constant	0.112***	0.082***	0.783***	2,745.920***
	(0.019)	(0.019)	(0.031)	(35.770)
Observations	15,554	15,554	11,476	9,633
R-squared	0.009	0.008	0.011	0.088

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Note: This table presents estimates from regression model (2). The first row presents $\gamma_{screening}$, rows 2 and 3 present $\gamma_{gpa_{q1}}$ and $\gamma_{gpa_{q2}}$. Column 1 considers the one-year dropout rate at any enrolled program among admitted students to Aarhus or Odense. Column 2 exclude transfers into other medical programs in measuring one-year dropouts. Column 3 and 4 analyze completion rate and time until completion among graduates, respectively. All columns pool enrolled students at both institutions.

This suggests than increasing the share of Quota 2 seats at Odense could improve average student outcomes there.

We expand the analysis in Table **??** in the main text using alternative measures of student quality. Specifically, we summarize ranked applicants into deciles or place students into ranked bins of 25 students each. A higher quintile or rank means a higher position in the ranking. We then regress a student's three-year dropout rate on the percentile or ranked bin, controlling for year by school fixed effects, resident location by school fixed effects, and year by GPA fixed effects.

We find that higher ranked students at Odense have lower dropout rates, see Panel B, column 1 in Table 13. For example, we find that being ranked in the next higher bin of 25 students is associated with a 0.7 percentage point reduction in the three-year dropout rate, statistically significant at 10% level. Higher ranked students at Odense also perform better at Aarhus, columns 2, and at other medical school programs more generally, columns 3, as indicated by lower dropout rates. For example, being ranked in the next higher bin of 25 students at Odense is associated with a statistically significant 2.5 p.p. reduction in the three-year dropout rate at other medical programs. The results in column 4 indicate that Odense's ranking is even predictive of persistence in non-medical degree programs, but here the coefficients are less precisely estimated.

We revisit these pattern for the quota 2 ranking at Aarhus in Table 14. Here the results are qualitatively the same but both the own and cross-program effects are typically smaller in magnitude, when compared to the evidence for Odense's ranking. For example, being ranked in the next higher bin of 25 students at Aarhus is associated with a statistically significant reduction in dropout rates at Aarhus of only 0.4 percentage points, see Panel B,

column 2.

Table 16 supplements Table 5 by analyzing the relative assessments of quota 2 applicants to both Copenhagen and Odense in Panel A, and to all three focal programs (Aarhus, Copenhagen, Odense) in Panel B. While the sample shrinks substantially in Panel B when selecting only applicants who submit three quota 2 applications, the qualitative patterns of the results are similar across panels and confirm the evidence in the main text. Conditional on rivals' signals, Odense's ranking of applicants is highly predictive of their study success. We also find evidence of informative signals at Copenhagen conditional on Odense's assessment, but their signal precision seems to be particularly strong in the period pre-2002 and weakens substantially after 2002 when Odense's screening reform helps them to extract more precise information.

C.3 Odense's Admission Reform and Odense's Dropout Rates

In this section, we conduct various robustness tests for the results in Table 3. First, we find a robust reduction in dropout rates when excluding standby admissions or excluding the year 2008, see Panel A of Table **??**, columns 2 and 3. Complementing the results in column 5 of Table3, we also find a similar reduction in dropout rates restricting the sample to older cohorts who first entered medical school until the mid-2000s, see Table **??**, column 4. These results hold similarly when excluding transfers from the dropout measure in columns 5-8. Finally, the effects are robust to including all medical schools in the sample, including Aalborg in the last years of the sample period, rather than focusing on Odense, Aarhus and Copenhagen, see Panel B.

Figure 18 provides robustness for the results in Figure 4. While Figure 18a replicates the result on 3-year dropout rates at Odense from the main text, Figure 18b provides analogous results when excluding transfers. Figures 18c and 18d provide time series evidence complementing the pooled results in Figure 4b. Since the number of Aarhus students previously rejected at Odense fluctuates over time and is low in the early years of the sample, the patterns are less precise when we pool 3 cohorts into one observation and plot average dropout rates over time. One reason for the fluctuations in the 1990s is also the fact that some low-performing students stayed enrolled to continue receiving study grants even if they were planning to drop out of the program eventually. When including all dropouts beyond the 3rd year of studies into the analysis as well, we find less noisy results in the pre-reform period and a striking increase in dropout rates after the screening reform, see Figure 18d.

Table 13: Quota 2 Ranking and Student Dropout Rates: Odense's Signal

VARIABLES	(1) Odense	(2) Other Med	(3) Non-Med	(4) Any Other
Panel A: Safe admission indicator				
better ranked	-0.033**	-0.003	-0.094*	-0.047**
	(0.016)	(0.027)	(0.051)	(0.023)
R-squared	0.227	0.358	0.299	0.269
Panel B: Top 50% Above the Bar				
better ranked	-0.028*	-0.037	-0.104*	-0.054**
	(0.015)	(0.025)	(0.055)	(0.023)
R-squared	0.227	0.361	0.298	0.270
Panel C: Rank quintiles				
better ranked	-0.067**	-0.063	-0.111	-0.100***
	(0.031)	(0.044)	(0.080)	(0.037)
R-squared	0.228	0.361	0.297	0.271
Observations	1,809	564	575	1,279

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 14: Quota 2 Ranking and Student Dropout Rates: Aarhus' Signal

VARIABLES	(1) Aarhus	(2) Other Med	(3) Non-Med	(4) Any Other
Panel A: Safe admission indicator				
better ranked	0.002	-0.038	-0.029	-0.048***
	(0.022)	(0.028)	(0.027)	(0.018)
R-squared	0.208	0.215	0.127	0.108
Panel B: Top 50% Above the Bar				
better ranked	-0.016	-0.035	-0.057***	-0.055***
	(0.020)	(0.022)	(0.022)	(0.015)
R-squared	0.208	0.215	0.127	0.109
Panel C: Rank quintiles				
better ranked	-0.029	-0.037	-0.069***	-0.078***
	(0.027)	(0.028)	(0.024)	(0.018)
R-squared	0.208	0.215	0.128	0.111
Observations	1,927	1,471	4,460	6,086

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 15: Quota 2 Ranking and Student Dropout Rates: Copenhagen's Signal

VARIABLES	(1) Copenhagen	(2) Other Med	(3) Non-Med	(4) Any Other
Panel A: Safe admission indicator				
better ranked	-0.044**	-0.061***	-0.052**	-0.078***
	(0.018)	(0.023)	(0.024)	(0.016)
R-squared	0.161	0.171	0.100	0.078
Panel B: Top 50% Above the Bar				
better ranked	-0.040**	-0.041	-0.042	-0.066***
	(0.017)	(0.025)	(0.029)	(0.019)
R-squared	0.161	0.170	0.100	0.078
Panel C: Rank quintiles				
better ranked	0.001	-0.078***	0.034**	-0.003
	(0.028)	(0.028)	(0.014)	(0.011)
R-squared	0.159	0.174	0.100	0.077
Observations	2,877	2,745	11,704	14,575

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

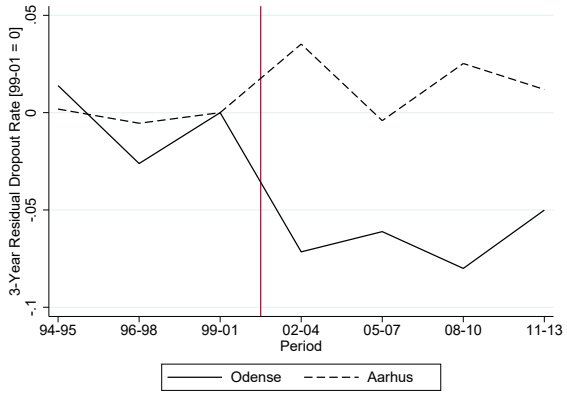
Table 16: Quota 2 Ranking and Student Dropout Rates: Pairwise Comparisons

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	ODE 1>2	Difference in 3Y Dropout for Student 1 versus Student 2				
Panel A: ODE and CPH	All	All	Both ODE	None ODE	Pre-2002	Post-2002
ODE Ranks 1>2		-0.077***	-0.008	-0.056***	-0.058**	-0.078***
		(0.015)	(0.017)	(0.022)	(0.024)	(0.017)
CPH Ranks 1>2	0.100***	-0.046***	-0.027*	-0.062***	-0.130***	-0.031**
	(0.017)	(0.014)	(0.016)	(0.022)	(0.032)	(0.015)
Observations	118,776	118,776	33,942	27,911	17,234	101,542
R-squared	0.036	0.045	0.058	0.080	0.108	0.047
Panel B: ODE, AAR and CPH	All	All	Both ODE	None ODE	Pre-2002	Post-2002
ODE Ranks 1>2		-0.110***	-0.029	-0.067**	-0.045	-0.116***
		(0.020)	(0.019)	(0.030)	(0.035)	(0.022)
AAR Ranks 1>2	0.054***	-0.010	-0.018	-0.006	0.030	-0.015
	(0.020)	(0.017)	(0.018)	(0.030)	(0.034)	(0.019)
CPH Ranks 1>2	0.081***	-0.034*	-0.028	-0.046	-0.123**	-0.023
	(0.020)	(0.019)	(0.023)	(0.031)	(0.052)	(0.021)
Observations	39,683	39,683	12,861	8,495	4,062	35,621
R-squared	0.051	0.083	0.118	0.122	0.159	0.095

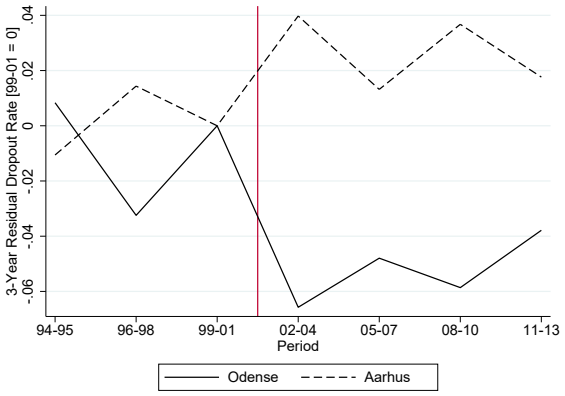
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

*Note: Panel A of Table 5 analyzes Copenhagen's and Odense's relative quota 2 rankings for pairs of quota 2 applicants to both programs, while Panel B analyzes pairs of quota 2 applicants to Copenhagen, Aarhus, and Odense. "ODE Ranks 1>2" is an indicator variable that takes value 1 if Odense assigns a higher quota 2 rank to candidate 1 than to candidate 2, and analogously for "CPH Ranks 1>2" and "AAR Ranks 1>2". Column 1 regresses the relative assessments of different programs on each other. The outcome of columns 2-6 is the difference in 3-year dropout rates within the pair, that is the outcome is 1 if candidate 1 drops out of their study program but candidate 2 persists, 0 if none of both candidates persist, and -1 if only candidate 2 drops out. All regressions control for cohort fixed effects, resident location fixed effects, and GPA fixed effects of each student in each pair. Standard errors reported in parentheses use two-way clustering at individual applicant level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

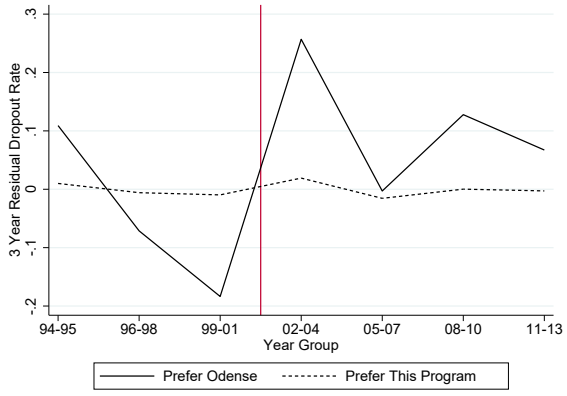
Figure 18: Dropout Rates by Medical Program Over Time



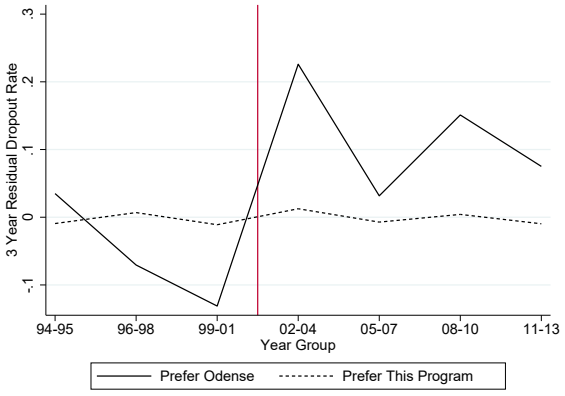
(a) Program-Specific 3-Year Dropout



(b) Any Dropout (incl. transfers until year 3)



(c) Program-Specific 3-Year Dropout



(d) Any Dropout (incl. transfers until year 3)

Note: Figures 18a and 18c plot the program-specific 3-year dropout rate of enrolled students over time, while Figure 18b and 18d measure all dropouts, including transfers withing the first three years of study or before the first BA degree, whichever comes first. The vertical axis in each graph reports average residual dropout rates after controlling for year and GPA fixed effects. The vertical lines denote the screening reform in Odense in 2002. Figures 18c and 18d focus on students enrolled at Aarhus University and distinguish students who preferred Aarhus or Odense at the time of their application based on the relative preference ranking. Figure 18c reports the 3-year dropout rate while Figure 18d reports results for all dropouts, including transfers within the first three years.

Table 17: Robustness: Odense's Dropout Rates and the Admission Reform

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
	3-Year Dropout Rate incl Transfers					3-Year Dropout Rate incl Transfers			
Panel A	Baseline	Excl Stby	Excl08	94-09		Baseline	Excl Stby	Excl08	94-09
postode	-0.072***	-0.061***	-0.071***	-0.082***	-0.046***	-0.040***	-0.046***	-0.056***	
	(0.015)	(0.016)	(0.015)	(0.016)	(0.014)	(0.015)	(0.015)	(0.016)	
Constant	0.135***	0.132***	0.137***	0.140***	0.121***	0.119***	0.123***	0.127***	
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	
Observations	18,114	16,349	17,124	13,403	18,114	16,349	17,124	13,403	
R-squared	0.049	0.053	0.046	0.052	0.047	0.051	0.045	0.050	
Panel B	Baseline	Excl Stby	Excl08	94-09		Baseline	Excl Stby	Excl08	94-09
postode	-0.072***	-0.061***	-0.071***	-0.082***	-0.046***	-0.039***	-0.045***	-0.056***	
	(0.015)	(0.016)	(0.015)	(0.016)	(0.014)	(0.015)	(0.015)	(0.016)	
Constant	0.135***	0.133***	0.137***	0.140***	0.122***	0.120***	0.123***	0.127***	
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	
Observations	18,319	16,541	17,329	13,403	18,319	16,541	17,329	13,403	
R-squared	0.048	0.052	0.046	0.052	0.046	0.050	0.044	0.050	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

C.4 Odense's Admission Reform and Aarhus' Dropout Rates

Table18 shows that the results remain largely unchanged when considering only the dropout outcome after the first admission to Aarhus for each student. The findings remain large in magnitude but become statistically insignificant when focusing on enrolled students after excluding transfers.

Table 18: Odense's Admission Reform and Performance of Students Admitted in Aarhus

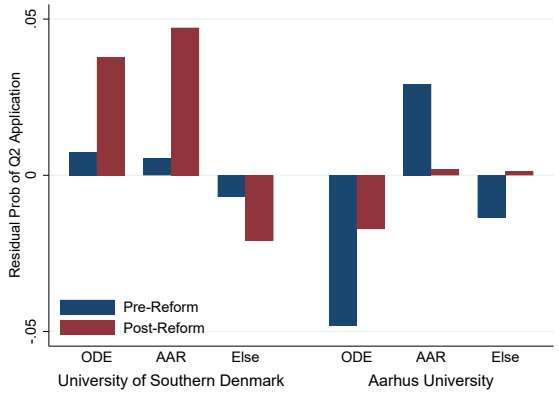
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	All	Ever Enrolled Med		Ever Enrolled AAR		Enrolled AAR	
	Full	1st obs	Full	1st obs	Full	1st obs	All	Excl Transfers
Prefer Odense	-0.064	-0.062	-0.051	-0.048	-0.052	-0.048	-0.051	-0.022
	(0.050)	(0.050)	(0.053)	(0.054)	(0.053)	(0.053)	(0.053)	(0.051)
Prefer Odense × Post	0.118**	0.110**	0.148**	0.141**	0.152**	0.145**	0.120**	0.084
	(0.054)	(0.055)	(0.059)	(0.060)	(0.059)	(0.060)	(0.061)	(0.059)
Constant	0.127***	0.127***	0.130***	0.130***	0.129***	0.130***	0.129***	0.118***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	7,482	7,147	6,814	6,497	6,755	6,441	6,342	6,342
R-squared	0.016	0.016	0.019	0.019	0.020	0.019	0.019	0.017

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

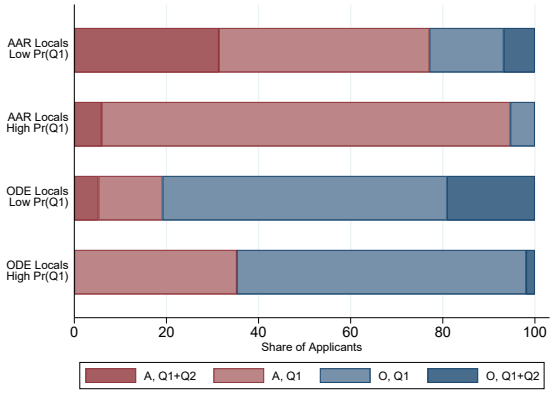
C.5 Details on Self-Selection and Quota 2 Admissions

Figure 19 provides additional evidence on the composition of quota 2 applicants, as well as the probability and composition of safe quota 2 admissions.

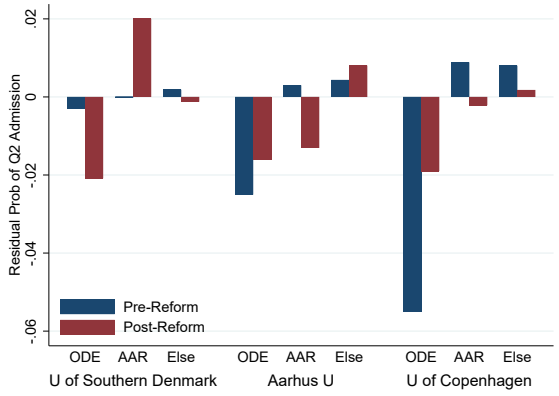
Figure 19: Quota 2 Applications and Admissions



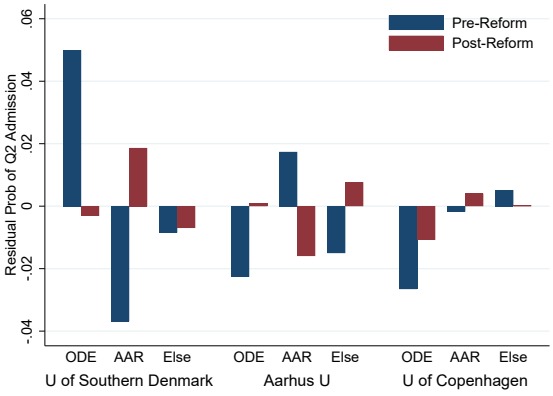
(a) Q2 Applications by Location



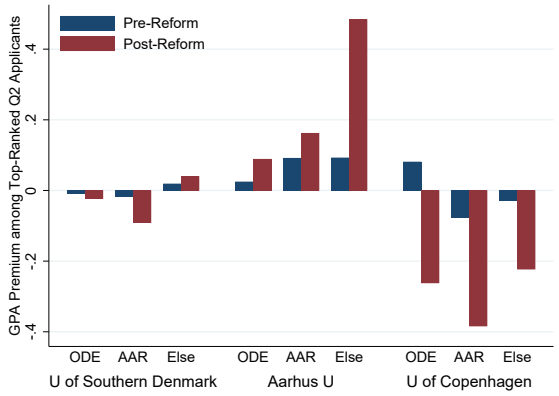
(b) Q2 Applications by Location and GPA



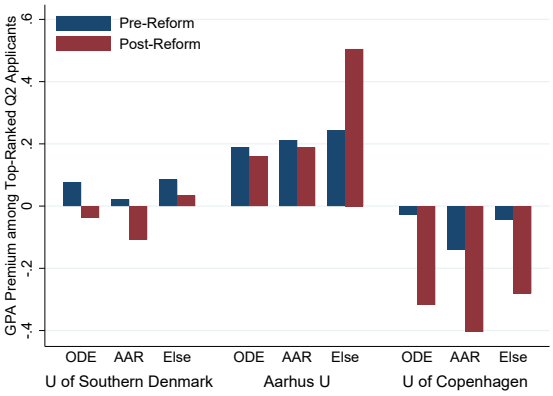
(c) Prob of Admission (above the bar)



(d) Prob of Safe Admission



(e) GPA Premium among Admissions

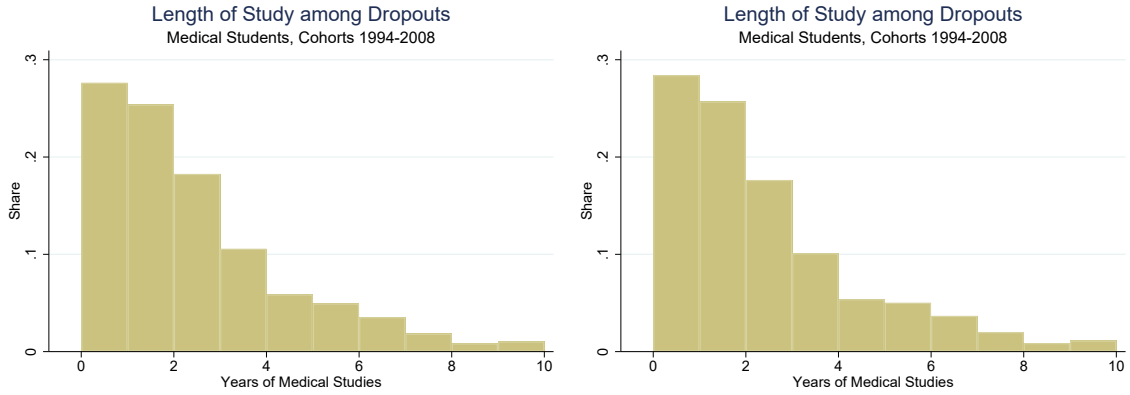


(f) GPA Premium among Safe Admissions

Note:.

C.6 Details on Dropouts

Figure 20: Distribution of Study Time until Dropout among Medical Students



(a) Program-Specific Dropout (b) Medicine Dropout

Notes: Data come from the Danish Higher Education Register (KOTRE). Figures 20a and 20b document the distribution of study time until dropout among medical students who exit before graduation. Figure 20a defines exit as leaving the program, which includes transfers, while Figure 20b is based on exits from the medical field of study. The sample includes cohorts that first enroll in medicine 1994-2006.

C.7 Evidence on Rejection Chains

For rejection chains to be attractive from a particular program's perspective (program P), several conditions have to be satisfied at the same time. In the data, we can analyze each one of them separately. Omitting Aalborg because of low case numbers, we focus on the remaining medicine programs, Odense (ODE), Copenhagen (COP), and Aarhus (AAR).

Suppose program P considers marginal candidate A. If P decides to strategically reject this candidate, a rejection chain can only be triggered if applicant A has applied to other medical programs (or relevant programs more broadly) in lower priority and will subsequently be admitted at one of these programs.

To assess this channel empirically, we measure the share of marginally rejected Q2 applicants at program P that is admitted in another medical program in the same year. To this end, we define marginal rejection as the 20 rejected students closest to the Q2 admission threshold in each year. The results in Table 19, Panel A, show that the flagship program in Copenhagen has the highest chance of triggering a rejection chain, because their high-caliber students would frequently be admitted to rival programs, especially through quota 2. In contrast, rejected candidates at Aarhus and Odense each have less than 10% chance of subsequently being admitted to another medical program.

Even if A gets admitted to another medical program, the rejection chain is only attractive if this admission leads to rejection of a candidate B at these other programs who in turn has applied to program P in a lower priority and would be admitted there. To assess the frequency of this condition being satisfied, we first measure the share of marginally admitted students (through both quota 1 and 2) at other medical programs that applied to program P in a lower priority. Panel B shows that about two-thirds of marginally admitted students through quota 1 at rival programs apply to Odense in a lower priority, but only one-third in the next lower priority. Aarhus is more frequently listed as the next lower priority among marginal students at rival programs. In contrast, a much lower share of students at Odense and Aarhus list Copenhagen as a lower priority, consistent with Copenhagen's flagship status. Panel C shows that the share of students admitted through quota 2 at rival programs who apply to other medical schools in lower priorities is substantially lower than among quota 1 students. 15-20% of students apply to another medical program as the next priority.

Finally, even if candidate B will now be available to program P as a result of the rejection chain, we need to determine if B will be preferred to the current marginal candidate by program P. Hence, we calculate the share of marginally admitted students in other programs that would have been admitted by program P through either quota 1 or quota 2. Panel D of Table 19 shows that 45% and 65% of marginal Q1 students from rival programs would be

admitted at Odense and Aarhus, respectively. The shares among marginal Q2 students at rival programs is considerably lower at 20% and 12% for Odense and Aarhus, respectively. Copenhagen is much more selective and would only admit 4-5% of marginal students at rival programs.

Table 19: Empirical Assessment of the Potential for Rejection Chains

Panel A: Marginally rejected students at program P			
Share admitted at rivals	Not admitted	Admitted through Q1	Admitted through Q2
Odense	90.10%	1.98%	7.92%
Copenhagen	51.75%	12.28%	35.96%
Aarhus	81.09%	2.99%	15.92%
Panel B: Marginally admitted students through quota 1 at other medical programs			
Share applied to P in lower priority	Did not apply	Applied at next prio	Applied at 2+ lower prio
Odense	40.62%	33.73%	25.65%
Copenhagen	72.55%	14.22%	13.24%
Aarhus	15.79%	62.35%	21.86%
Panel C: Marginally admitted students through quota 2 at other medical programs			
Share applied to P in lower priority	Did not apply	Applied at next prio	Applied at 2+ lower prio
Odense	80.14%	15.88%	3.97%
Copenhagen	71.47%	15.49%	13.04%
Aarhus	63.85%	19.49%	16.67%
Panel D: Marginally admitted students at other medical programs who apply to program P			
Share admitted to P	Q1 students at rivals	Q2 students at rivals	
Odense	42.04%	22.92%	
Copenhagen	3.92%	4.45%	
Aarhus	71.26%	13.33%	
Panel E: Benchmarking the share of successful chains			
Share of successful rejection chains if...	...all rejected candidates in Panel A trigger a chain	...all new candidates in Panel B+C preferred	
Odense	2.65%	1.93%	
Copenhagen	2.08%	7.32%	
Aarhus	4.25%	4.96%	

To assess the overall attractiveness of rejection chains, we consider two benchmark scenarios in Panel E of Table 19. Take Odense as an example. If all rejected candidates A trigger a rejection chain that allows Odense to assess a new candidate who would have otherwise been admitted at the rival program, then the probability of admitting a student preferred to A is $0.02 * 0.42 + 0.079 * 0.229 = 2.65\%$. But since admission at medical schools is very competitive, those who do not list Odense as their next priority will likely be admitted to a different program. In that sense, the 2.65% success rate is an upper bound. The analogous bounds for Aarhus and Copenhagen are 4.25% and 2.1%, respectively. Even though Copenhagen can place a much higher share of rejected students in rival programs (Panel A), the probability of finding a preferred candidate who was previously rejected at Odense or

Aarhus is low because they are highly selective as evidenced in Panel D.

As an alternative benchmark, we can restrict attention to students who apply to Odense as the next lower priority. Even if all of them would be admitted as preferred students over A, the success rate for a rejection chain triggered by Odense is only $0.02 * 0.342 + 0.079 * 0.159 = 1.9\%$. The analogous bounds for Aarhus and Copenhagen are 4.9% and 7.3%, respectively.

In sum, our analysis suggests that the potential of successful rejection chains may be limited in practice.

Table 20: Details on GPA Bins for Structural Estimation

Post Reform	Bin	Floor	Ceiling	$Pr[GPA > \underline{GPA_{Ode}}]$	$Pr[GPA > \underline{GPA_{Aar}}]$	$Pr[\underline{GPA_{Ode}} > GPA > \underline{GPA_{Aar}}]$	$Pr[\underline{GPA_{Aar}} > GPA > \underline{GPA_{Ode}}]$	$Pr[GPA < \min(\underline{GPA_{Ode}}, \underline{GPA_{Aar}}]$
0	0		8.8	0	0	0	0	1
0	1	8.8	95	0.751	0.243	0	0.508	0.249
0	2	9.5	9.8	0.999	0.842	0	0.158	0
0	3	9.8		0.999	0.999	0	0	0
1	0		8.8	0	0.007	0.007	0	0.993
1	1	8.8	95	0.334	0.242	0.009	0.101	0.657
1	2	9.5	9.8	0.581	0.653	0.082	0.01	0.337
1	3	9.8		0.906	0.904	0.027	0.029	0.067

D Quota 2 Applications

Once students learn which programs j satisfy $u_j > 0$, they investigate these programs and learn quota-2 application costs only for these programs. Students choose a subset of their quota 1 applications to which to apply to via quota 2, in order to maximize their expected utility net of application costs.

Without loss of generality suppose that a student prefers program 1 to program 2 (the case 2 is preferred to 1 is analogous). Define the following probabilities of offers conditional on quota-2 application decisions and student preferences:

$$\begin{aligned}
Pr(1|\emptyset) &= \widehat{Pr}(gpa_i \geq \underline{gpa}_1) \\
Pr(2|\emptyset) &= \widehat{Pr}(\underline{gpa}_1 > gpa_i \geq \underline{gpa}_2) \\
Pr(1|\{1\}) &= Pr(1|\emptyset) + (1 - Pr(1|\emptyset))(1 - F_{s_1|\epsilon^u}(\underline{s}_{1t}(x))) \\
Pr(2|\{1\}) &= F_{s_1|\epsilon^u}(\underline{s}_{1t}(x))Pr(2|\emptyset) \\
Pr(1|\{2\}) &= Pr(1|\emptyset) \\
Pr(2|\{2\}) &= Pr(2|\emptyset) + \widehat{Pr}(gpa_i < \min(\underline{gpa}_1, \underline{gpa}_2))(1 - F_{s_2|\epsilon^u}(\underline{s}_{2t}(x))) \\
Pr(1|\{1,2\}) &= Pr(1|1) \\
Pr(2|\{1,2\}) &= F_{s_1|\epsilon^u}(\underline{s}_{1t}(x)) \times \Big(Pr(2|\emptyset) \\
&\quad + \widehat{Pr}(gpa_i < \min(\underline{gpa}_1, \underline{gpa}_2) \times Pr(s_2 \geq \underline{s}_{2t}(x) | s_1 < \underline{s}_{1t}(x), \epsilon^u) \Big)
\end{aligned}$$

There are three different cases to be considered. First, if a student does not submit any quota-1 applications, there is no decision to make and no quota 2 application is submitted. Second, if the student applies to a single program $j = 1$ via quota 1, then the student submits a quota 2 application iff

$$u_j \times \Big(Pr(j|\{j\}) - Pr(j|\emptyset) \Big) > c_{\{j\}}. \tag{26}$$

Third, if the student applies to both programs, then define

$$v_a = Pr(1|a) \times u_1 + Pr(2|a) \times u_2 - c_{\{a\}} \ , \tag{27}$$

for quota 2 application portfolio a. $c_{\{a\}}$ denotes the sum of application cost over all quota 2 applications in a. The optimal portfolio satisfies

$$v_{a'} - v_a \leq 0$$

for all $a' \neq a$.