Interdependent Values in Matching Markets: Evidence from Medical School Programs in Denmark*

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

October 26, 2021

Click here for most recent version

Abstract

This paper studies interdependent values 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. Our findings suggest that both sources play a role and that programs benefit from learning information rival programs hold as well as learning about student preferences in identifying students with higher completion rates.

*We thank seminar participants at Penn, Northwestern University and University of Michigan. We thank the Department of Economics and Business, Aarhus University, and VIVE Denmark for invaluable support and making the data available.

[†]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

The Danish school system is organized into 9 years of compulsory primary and lower secondary education, for children aged 6-15, and upper secondary education for young people aged 16-19. More that 50% of the student cohort completes a general upper secondary education program (high school education) (Daly and Le Maire, 2019), which is a pre-requisite for access to university education.[4] With few exceptions, the education system is governmentally funded and students above the age of 17 qualify for financial assistance while in school. All university applications are handled through a centralized admission system. As in most European countries, Danish students decide which programs and thereby geographical location they would like to enroll in when they apply for university admission. Each

et al. (2020).

[4]The remaining may complete a vocational upper education program, which qualifies students for a career in a specific trade or industry (Nusche, 2016).

applicant submits an ordinal ranking of their (up to) 8 most preferred programs, where a program denotes a field of study (e.g. medicine) at a specific institution (e.g. University of Copenhagen).

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 determined in advance by a government agency to meet the future public demand of health care professionals (e.g. physicians). The total number of program seats is divided into two admission channels, quota 1 seats and quota 2 seats. Quota 1 seats are allocated purely on the grounds of the applicants' high-school GPA. Quota 2 seats are granted to applicants who do not meet the GPA requirements of quota 1; rather quota 2 students are admitted based on assessment of cognitive skills, motivation and past experience. Details of the administration and scoring of the quota 2 admission criteria differ across programs. In the context of medicine programs, quota 2 admission typically involves the assessment of a motivational letter and extra-curricular activities (mainly work-experience, volunteering, exchange experience and additional academic qualifications), as well as potentially additional tests and interviews.

The medical programs have their own quota 2 assessment committees evaluating applicants. Programs determine the fraction of college seats that are assigned to quota 1 and quota 2, respectively, subject to national higher education regulation.[5] The application deadline for quota 2 students is four months prior (mid-March) to the quota 1 application deadline (early July). The quota 1 to 2 ratio are determined by the programs in March-April, within the limits of federal higher education regulations. This is after the application deadline of quota 2 (March 15) but before the programs have time to process the applications.

All quota 2 applicants are automatically considered for quota 1 application by the Danish Central Admissions Secretariat (CAS). If the number of applicants exceeds the number of quota 1 seats, admission through quota 1 is restricted and only students whose high school GPA exceeds the program- and year-specific GPA cutoff will receive an offer of admission. 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

[5] 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%.

through quota 2. Programs review the quota 2 applications and submit a rank-order over students to CAS. Importantly, programs cannot use the student's preference ranking, which we observe as detailed below, in their rank-order over students. Some medicine programs also maintain a quota 2 stand-by list.

2.2 Matching and the Deferred Acceptance Algorithm

CAS aggregates the quota 1 rank-order list and the quota 2 applications submitted by students as well as the programs' quota-specific rankings over students and assigns students based on a student-proposing deferred acceptance (DA) algorithm.

On the student side, CAS combines a student's quota 1 and quota 2 applications by extending their quota 1 program rank-order list and incorporating the quota 2 application decisions. 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. Recall that the original rank-order list includes all programs that received a quota 2 application from the student. This maintains the reported preference priority between programs and imposes a priority for quota 1 admissions over quota 2 admissions.[6] Treating quota 1 and quota 2 admissions as separate pseudo-programs, this yields a maximum of $8 + 8 = 16$ program-by-quota student applications that can be considered by CAS.

On the program side, CAS records the program's ranking over quota 2 applicants. For quota 1 applicants, programs (passively) rank applicants purely based on the student's GPA. Together, this provides CAS with an extended student rank-order list over all pseudo-programs as well as a program ranking over applicants for each pseudo-program. Finally, students are assigned to programs based on a student-proposing deferred acceptance (DA) algorithm, which we explain further in the next section.

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. The student can then decide to accept (enroll) or reject, 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. Throughout our factual analysis, we assume that students truthfully report their preferences in the quota 1 rank-order list, which is a weakly dominant strategy in the game induced by a student-proposing DA algorithm (Roth, 1982) assuming that quota 1

[6]For example, suppose that student i applied to programs $4, 7$ and 2 via quota 2 and submitted the quota 1 rank-order list is $l_i = \{4, 3, 7, 2\}$, where the numbers correspond to distinct programs. The extended program ranking is then $l_i^{ext} = \{4^{Q1}, 4^{Q2}, 3^{Q1}, 7^{Q1}, 7^{Q2}, 2^{Q1}, 2^{Q2}\}$, where $Q1$ denotes a quota 1 application and $Q2$ denotes a quota 2 application.

applications are free of cost. In contrast, quota 2 applications are not necessarily free of cost and we carefully consider the student's strategic tradeoffs inherent to the quota 2 application decisions in the remainder of the analysis.

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).[7]

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., 2011a; 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).[8] 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

[7] 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.

[8] 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.

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.[9] 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.

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. (2011b). 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

[9] 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.

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),

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

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 $k \in \{0, 1, 2\}$.[10] 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 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.

[10] 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.

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[11]

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

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).[12] Where the meaning is clear, we may omit (ℓ, a, r) and write $D_j^q(x, \underline{r})$ for

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

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

$$D_j^2(x, \underline{r}; \ell, a, r) = (X = x) \cap (\{a_j = 1\} \cap \{r_j^1(x) < \underline{r}_j^1\}) \cap \\ \left(\{\ell_i : j \succ k\} \cup (\{a_k = 0\} \cap \{r_k^1(s_k, x) < \underline{r}_k^1\}) \cup (\{r_k^2(s_k, x) < \underline{r}_k\} \cap \{r_k^1(s_k, x) < \underline{r}_k)\}\right)$$

brevity.

We now state programs' payoffs. Pseudoprogram (j,q) receives ω_j from each student it 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.[13] We believe this

$$D_j^1(x,\underline{r};\ell,a,r) = (X=x)\cap\{\ell_i : j \succ 0\}\cap(\{\ell_i : j \succ k\}\cup$$
$$(\{a_k=0\}\cap\{r_k^1(s_k,x)<\underline{r}_k^1\})\cup(\{r_k^2(s_k,x)<\underline{r}_k\}\cap\{r_k^1(s_k,x)<\underline{r}_k\}).$$

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

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

[13] In general, in many-to-one stable matching mechanisms, programs may have incentives to engage in ca-

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 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

pacity 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.

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 at least one medical school program in their submitted preference ranking.[14] 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.[15] 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

[14] 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.

[15] 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.

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.[16]

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 program ranking. For Aarhus and Odense this share drops to 44.6% and 28.9%. 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 list a flagship program first and Aarhaus second (A and A2), the share that list Odense first or list a flagship program 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 at only 15.5%, consistent with their 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

[16] 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.

Table 1: Summary Statistics: Medical School Applicants

	Copenhagen	Aarhus	Odense	Aalborg
Applicants	30,356	25,328	22,497	3,737
Share listing j as 1st Priority	0.68	0.446	0.289	0.163
Share submitting Quota 2 Application to j	0.617	0.338	0.155	0.571
Admitted	9,475	6,949	4,680	214
Admitted via Q1	7,723	5,357	2,791	191
GPA Cutoff Q1	9.852	9.617	9.513	10.361[†]
Enrolled	7,927	6,477	4,170	206
1y Dropout Rate	0.05	0.055	0.05	0.102
3y Dropout Rate	0.121	0.132	0.122	0.165
1y Transfer Rate	0.003	0.004	0.006	.[§]
3y Transfer Rate	0.005	0.012	0.017	.[§]
10y Completion Rate	0.832	0.838	0.829	.[‡]
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 14e.* [§]*: 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.*

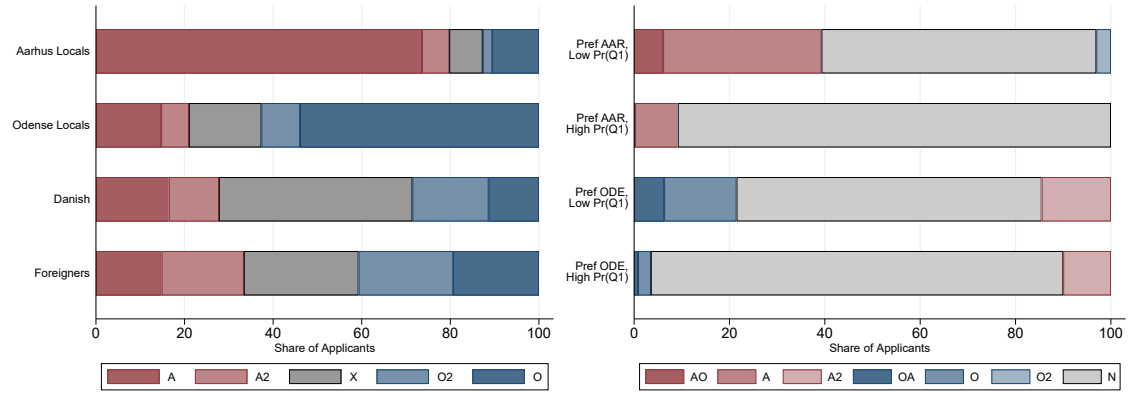
2. Nevertheless, a large share of students with low GPA also rely on quota 1 applications only, consistent with applicants being unconstrained in their priority lists. Finally, Figure 1b shows that quota 2 applications to Aarhus are much more frequent and even students who prefer Odense often only apply 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 23% of the applicants are admitted to any medical school program, see Table 1. The largest program is Copenhagen (≈ 475 admissions per year) followed by Aarhus (≈350 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 14a 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 9. 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 14b.

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.[17]

[17]GPA cutoffs have been increasing over the sample period due to an increase an applications, which

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.

About 88% of admitted students enroll in the program.

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.

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 14e.

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 10. 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 0.6% of rejected students at Odense are admitted to Copenhagen, reducing the potential importance of a winner's curse. This share increases more than fourfold to 2.6% when considering admissions to Aarhus. Similarly, about 4.4% 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. Recall that quota 1 admissions purely depend on GPA as evidenced in Figure 2a, which plots the fraction of admitted applicants to Odense or Aarhus 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. As the GPA passes the GPA threshold, the probability of being admitted via quota 1 quickly shoots to 100 percent. Quota 2 admission chances also depend on the GPA, as indicated by the upward-sloping relationship in admission chances below the cutoff, but not only. We find differences in the quota 2 admission chance when splitting this graph out by program. At Odense, quota 2 applicants have a relatively high admission chance. That is true for students with a GPA relatively close to the cutoff, see Figure 2c, but also overall. The average quota 2 admission chance among quota 2 applicants to Odense equals 83.2%. However, we find no evidence for an increase in quota 2 admission chances in the GPA. At Aarhus on the other hand, the average admission chance is only 37.3% (among all applicants) and this probability increases from 20% to about 50% among these students as the GPA reaches the cutoff, see Figure 2e.

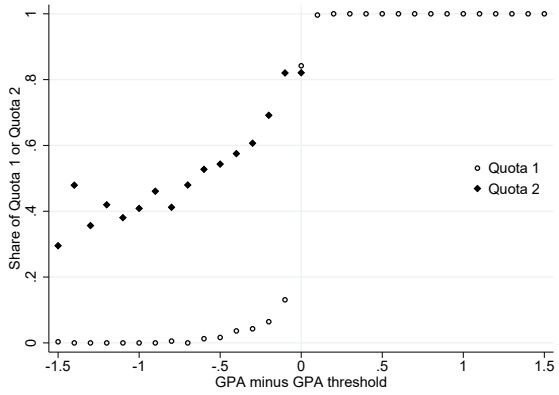
To test whether the additional and admission-relevant information collected through the quota 2 review process is correlated with student persistence, we test for differences in dropout rates among admitted students at the GPA cutoff. Figure 2b presents a sharp difference in the three year-dropout rate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

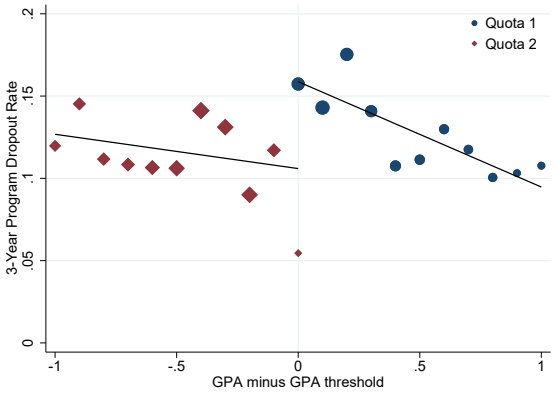
$$\begin{aligned} Y_{ijt} &= \gamma_0 + \gamma_{gpa_{q1}} \cdot gpa_i \cdot \mathbb{1}\{GPA \geq cutoff\} + \gamma_{gpa_{q2}} \cdot gpa_i \cdot \mathbb{1}\{GPA < cutoff\} \\ &+ \gamma_s \cdot \mathbb{1}\{GPA < cutoff\} + \gamma_{jt} + \epsilon_{ijt}, \end{aligned} \tag{2}$$

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

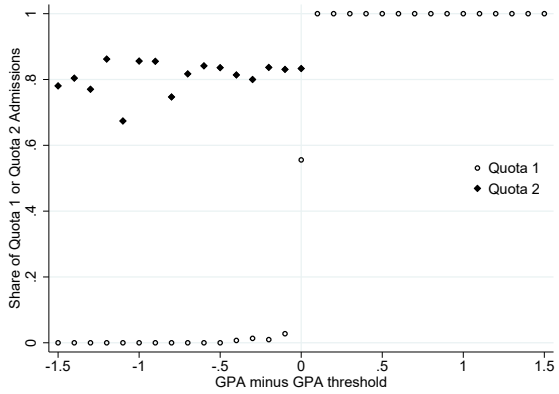
Figure 2: Admissions and Dropouts by Quota



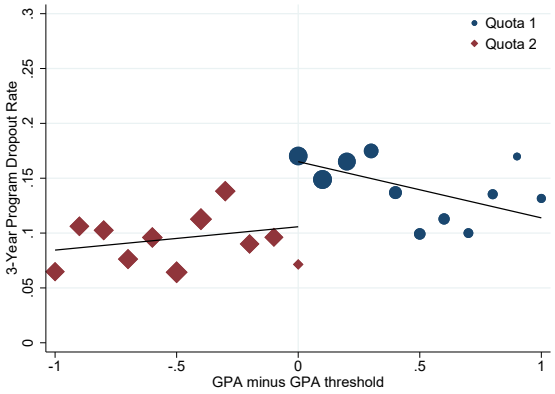
(a) Admissions and Distance to Cutoff



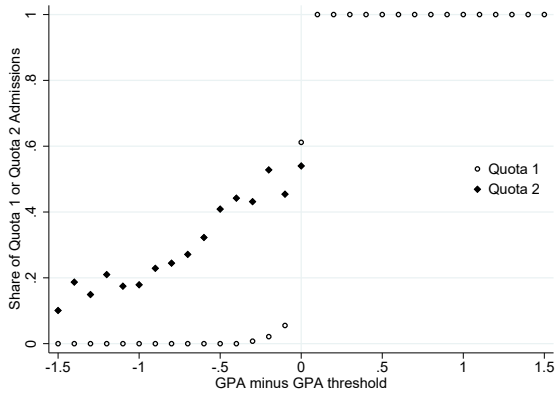
(b) Dropouts by Distance to Cutoff



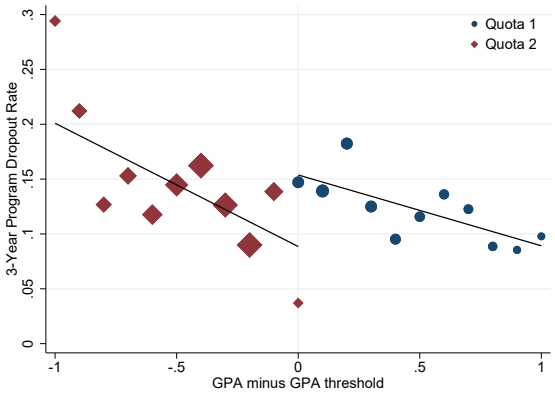
(c) Admissions by Quota and GPA: Odense



(d) Dropouts by Distance to Cutoff: Odense



(e) Admissions by Quota and GPA: Aarhus



(f) Dropouts by Distance to Cutoff: Aarhus

Note: Figure 2a plots the fraction of admitted applicants to Aarhus or Odense 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 2c and 2e split this out for students admitted to Odense and Aarhus, respectively. Figure 2b maintains the same horizontal axis but plots the 3-year dropout rate on the vertical axis. 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. Figures 2d and 2f show separate results for students in Odense and Aarhus, respectively.

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 6.1 p.p. lower three-year dropout rate than students admitted via quota 1, see column 1. This difference falls slightly to 5.1 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 11.

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. Mirroring the regression evidence, Figure 2f illustrates a steep increase in the dropout rate among lower-GPA students admitted via quota 2 at Aarhus, whereas Figure 2d shows constant dropout rates by GPA among quota 2 students at Odense.

Table 2: Programs' Information Quality and Student Dropout Rates

	(1)	(2)	(3)	(4)
	3Y Dropout	3Y Med Dropout	3Y Dropout (AAR)	3Y Dropout (ODE)
γ_s	-0.061***	-0.051***	-0.073***	-0.061***
	(0.015)	(0.015)	(0.021)	(0.023)
$\gamma_{gpa_{q1}}$	-0.005***	-0.005***	-0.006***	-0.003
	(0.001)	(0.001)	(0.002)	(0.003)
$\gamma_{gpa_{q2}}$	-0.003	-0.002	-0.011***	-0.001
	(0.002)	(0.002)	(0.004)	(0.003)
Constant	0.219***	0.136***	0.179***	0.265***
	(0.020)	(0.019)	(0.025)	(0.029)
Observations	8,855	8,855	5,531	3,324

*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, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

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 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 12 for details. This suggests that differences in student selection may contribute to the observed difference but cannot explain it in full.

We also explore the correlation between the program ranking and dropouts. To this end, we first define an indicator variable for safe admission via quota 2 that takes value 1 if a student ranks within the K_{jt} first positions on the program ranking and zero otherwise, where K_{jt} denotes the program's capacity of quota 2 seats in the given year. We then regress the student's three-year dropout indicator on the safe-admission indicator, controlling for year by school fixed effects, resident location by school fixed effects, and year by GPA fixed effects. Table 3 reports the results for quota 2 applicants to Aarhus (columns 1-3) and to Odense (columns 4-6), respectively.

Being ranked among the top quota 2 candidates at Odense is associated with a statistically significant 3.5 percentage points lower 3-year dropout rate among students who enroll at Odense, column 1. A top ranking by Odense also predicts a 2.5 percentage points lower dropout rate among students, who enroll at Aarhus but this results is not precisely estimated in this small sample, column 2. Yet, more generally, Odense's assessment is predictive of student performance at any other program as evidenced by a 5.9 percentage points lower dropout rate in column 3. In contrast, we find an imprecisely estimated positive relationship between receiving a top ranking at Aarhus and 3-year dropout rates among students who enroll in the program. Nevertheless, we find suggestive evidence in columns 5 and 6 that Aarhus' ranking also predicts student success at Odense and other programs more generally.

Appendix Tables 13 and 14 show that these results are robust to alternative measures of student quality as assessed by the programs. Specifically, we repeat the analysis either summarizing ranked applicants into quintiles or placing students into ranked bins of 25 students each. A higher quintile or rank means a higher position in the ranking. We find strong evidence that higher ranked students at Odense have lower dropout rates. While the results are qualitatively the same at Aarhus, both the own and cross-program effects on dropouts are smaller in magnitude, when compared to the evidence for Odense's ranking.

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 9 for details.

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,

Table 3: Quota 2 Ranking and Student Dropout Rates: Safe Admission Rank

	(1)	(2)	(3)	(4)	(5)	(6)
	Odense Ranking			Aarhus Ranking		
	Odense	Aarhus	Not Odense	Aarhus	Odense	Not Aarhus
1{safe Q2 rank}	-0.035**	-0.025	-0.059***	0.022	-0.031	-0.034*
	(0.016)	(0.059)	(0.023)	(0.028)	(0.050)	(0.020)
R-squared	0.210	0.533	0.265	0.202	0.306	0.096
Observations	2,203	250	1,536	1,698	883	7,652

*Note: Table 3 presents the effects of Odense's quota 2 ranking on an indicator for receiving a safe rank that guarantees admission given capacity, controlling for year by school fixed effects, resident location by school fixed effects, and year by GPA fixed effects. Columns 1-3 consider quota 2 applicants at Odense and report their dropout outcomes if they are admitted at Odense, column 1, at Aarhus, column 2, or any program except Odense, column 3. Mirroring this structure, columns 4-6 consider quota 2 applicants at Aarhus and report their dropout outcomes if they are admitted at Aarhus, column 4, at Odense, column 5, or any program except Aarhus, column 6. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

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 3a presents the 3-year dropout rates among enrolled students by program and the start year (cohort).[18] 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 in the two programs before 2002, Figure 3a 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.

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

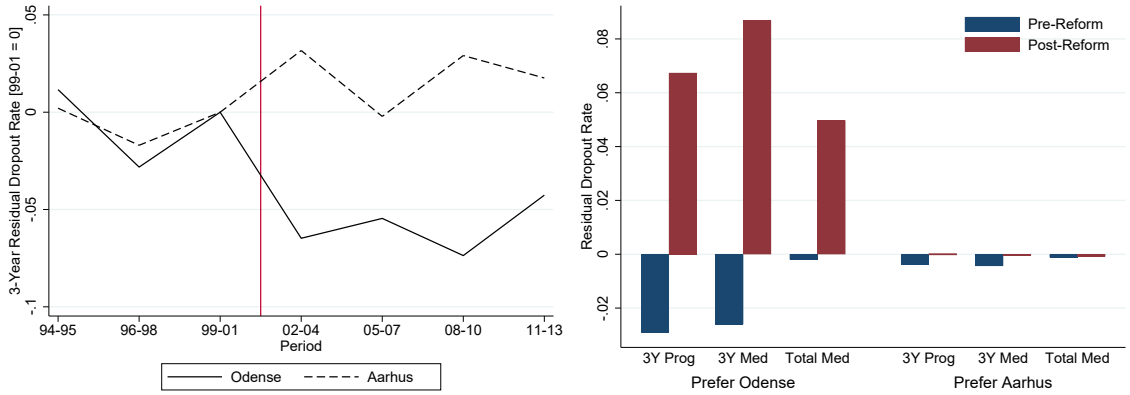
$$Y_{ijt} = \gamma_j + X'_{ijt}\gamma_c + \gamma_P \cdot Post_t + \gamma_{DID} \cdot Post_t \cdot Odense_j + \epsilon_{jt}, \tag{3}$$

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 4 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 5.1 p.p. and the three-year dropout

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

Figure 3: 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 Figures 3a and 3b delineate the timing of Odense's admission reform.

Table 4: 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
postode	-0.051***	-0.071***	-0.039***	-0.047***	0.051**	-159.186***
	(0.011)	(0.017)	(0.011)	(0.016)	(0.020)	(21.730)
Observations	10,497	10,497	10,497	10,497	7,714	6,431
R-squared	0.059	0.073	0.056	0.070	0.077	0.152

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 5: 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, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

rate falls by 7.1 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, and alternative persistence measures, see Appendix Table 15. Our results are also robust to extending our program specific dropout measure to dropouts from any medical school program, see Appendix Table 16.

Together, the evidence from Figure 3 and Table 4 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 interdependent 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 who prefer Aarhus over Odense 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 3b presents the residual dropout rate, after controlling for year and GPA fixed effects, among enrolled students in Aarhus by their reported preferences. 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 15. The right-hand side reports outcomes for students who prefer Aarhus over Odense. Here, we see stable outcomes over time. This stands in sharp contrast to persistence for students who prefer Odense but were not admitted to Odense, denoted on the left side of the figure. Following the reform, we see a striking increase in dropout rates of up to 10 percentage points, providing first evidence for an increase in adverse selection. This is true after excluding program transfers (3Y med) and when including later program dropouts in study years 4 and onward (Total Med).

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 5 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 12.3 p.p. in the post-reform period, relative to students who prefer Aarhus, see column 1. 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 drops slightly when only considering students who enroll in the same year at Aarhus. 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 3a, and the increase in dropout rates Aarhus among students who prefer Odense over Aarhus, Figure 3b, 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 Admissions and the Home Bias

Building on these insights, we next explore whether program's admission decisions 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 4a we consider the probability of quota 2 admission conditional on the student's region of residence, after controlling for fixed effects for cohort and student gpa. 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 admission chances. Conversely, students from Aarhus have the lowest admission chances. This pattern is reversed (at smaller magnitudes) in the post-reform years. Now students from Aarhus have a higher admission chance than students from Odense.[20] 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 admission decisions but less so in the post-reform years as Odense collects a more informative signal of student persistence.

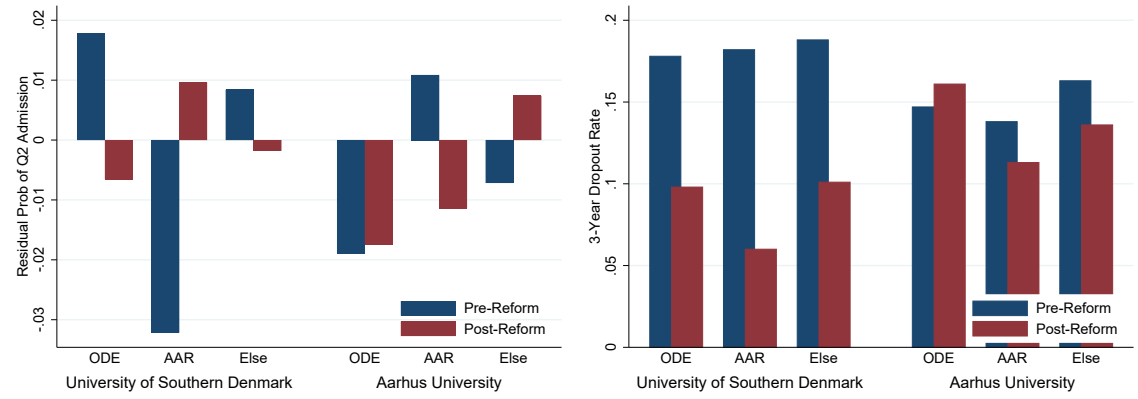
Turning to Aarhus, we also find evidence for a home bias in the pre-reform years as indicated in the right part of Figure 4a. Students from Aarhus have the highest admission chances when compared to students from Odense and other regions. This bias flips sign in the post-reform years in favor of students from other regions. Students from Odense receive a similar penalty in both the pre- and post-reform period. 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 4b, we compare dropout rates by region of origin over time. Consistent with 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.

[20] We see qualitatively similar patterns, when considering an alternative metric of admission preferences, the chance of a safe spot defined as a rank below the total number of available quota 2 seats, see Figure 16c

Figure 4: Program Preferences and Quota 2 Applications



(a) Quota 2 Admission Chance

(b) Dropouts by Former Residence

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 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 determine whether Odense ranks candidate 1 above candidate 2 or vice versa, and analogously whether Aarhus ranks candidate 1 above candidate 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.

Our unit of analysis is then a pair of applicants who apply through quota 2 to both programs in a given year. We construct two indicators that turn on if Odense ranks student 1 above student 2 and if Aarhus ranks student 1 above student 2. 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 6, 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 4.5 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 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 return to the full sample of pairs and test for changes in the ranking precision between the pre- and post reform period, see column 5. For Odense, the coefficient increases from 6 p.p. to 6p.p.+6.5p.p.=12.5p.p. in the post-reform period, significant at 1% level. The effect for Aarhus increases by 5.9 p.p. but post-reform screening remains statistically insignificant.

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 Aarhus. In other words, this suggests that Aarhus 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. Our findings also suggest that both programs have some private information about completion 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 7 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 ranks a

Table 6: Quota 2 Ranking and Student Dropout Rates: Pairwise Comparisons

	(1)	(2)	(3)	(4)	(5)
Outcome	AAR 1>2	Difference in 3Y Dropout for Student 1 versus Student 2			
Sample	All	All	Both ODE	None ODE	All
ODE Ranks 1>2	0.045**	-0.120***	-0.031*	-0.052*	-0.060
	(0.018)	(0.019)	(0.018)	(0.028)	(0.046)
AAR Ranks 1>2		-0.015	-0.015	-0.040	0.039
		(0.017)	(0.018)	(0.028)	(0.039)
ODE Ranks 1>2 Post					-0.065
					(0.050)
AAR Ranks 1>2 Post					-0.059
					(0.042)
Observations	62,394	62,394	21,053	12,564	62,394
R-squared	0.037	0.063	0.085	0.104	0.064

*Note: Table 6 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, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

different medical program higher. We find that students who also applied via quota 2 have a 2.1 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.

We also find that 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

Table 7: 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	-0.021*	-0.025**	-0.021*	-0.025**	0.025	0.030*	-12.941	-19.180
	(0.011)	(0.012)	(0.011)	(0.011)	(0.016)	(0.017)	(17.491)	(18.316)
Prefer Other Prog	0.053**	0.023	0.003	-0.011	-0.002	0.017	71.001**	-8.815
	(0.025)	(0.027)	(0.024)	(0.026)	(0.029)	(0.032)	(32.547)	(35.589)
Constant	0.137***	0.137***	0.125***	0.125***	0.825***	0.826***	2,567***	2,569***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(6.443)	(6.502)
Add Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	7,038	6,975	7,038	6,975	5,014	4,960	4,152	4,119
R-squared	0.011	0.026	0.008	0.022	0.007	0.026	0.065	0.093

*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, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

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.[21]

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).

[21] 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 14e. See Appendix Table 19 for more details.

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:

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

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, $\Theta_2 = \{\gamma_j, \rho_{ej}, \delta_{jt}, \sigma_{ct}, \sigma_{c12t}\}$ 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 es-

timate 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 E.

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 8 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

Table 8: 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, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

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 on GPA, which ranges from 0 for low GPAs to 3 for high GPAs as discussed above.[22] 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 2d and may help reconcile why quota 2 admission chances to Odense are not systematically related to the GPA, Figure 2c, 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 4a, 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

[22]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.

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 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.

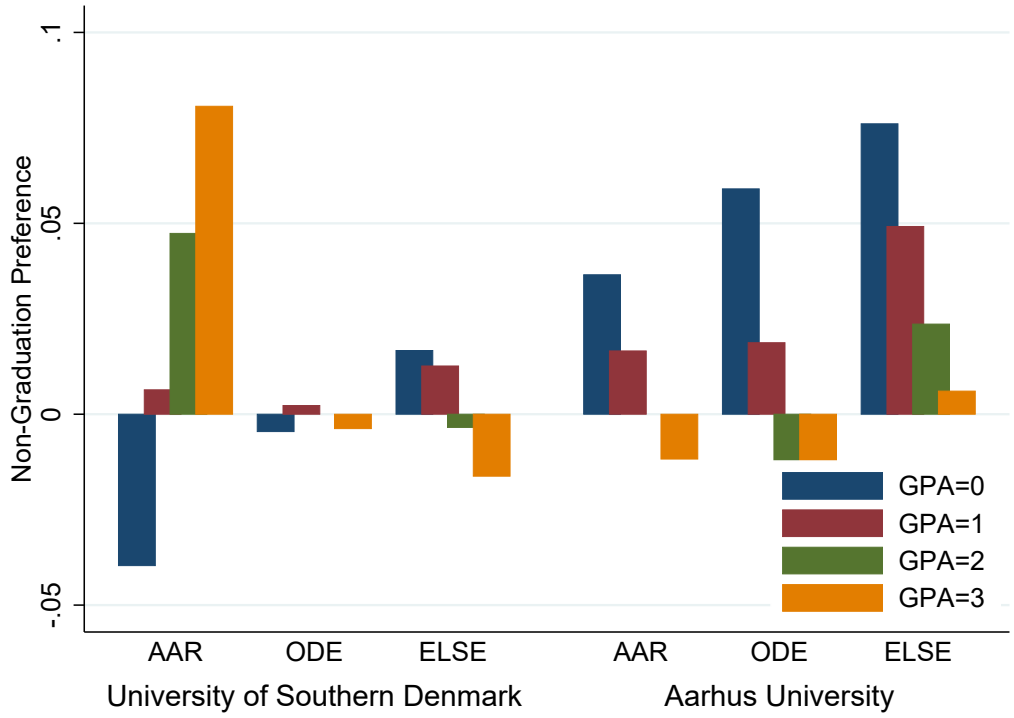
7.2.2 Program Objectives in the Post-Period

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 5 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 20.

Figure 5: Non-Graduation Preferences: Post-reform Period



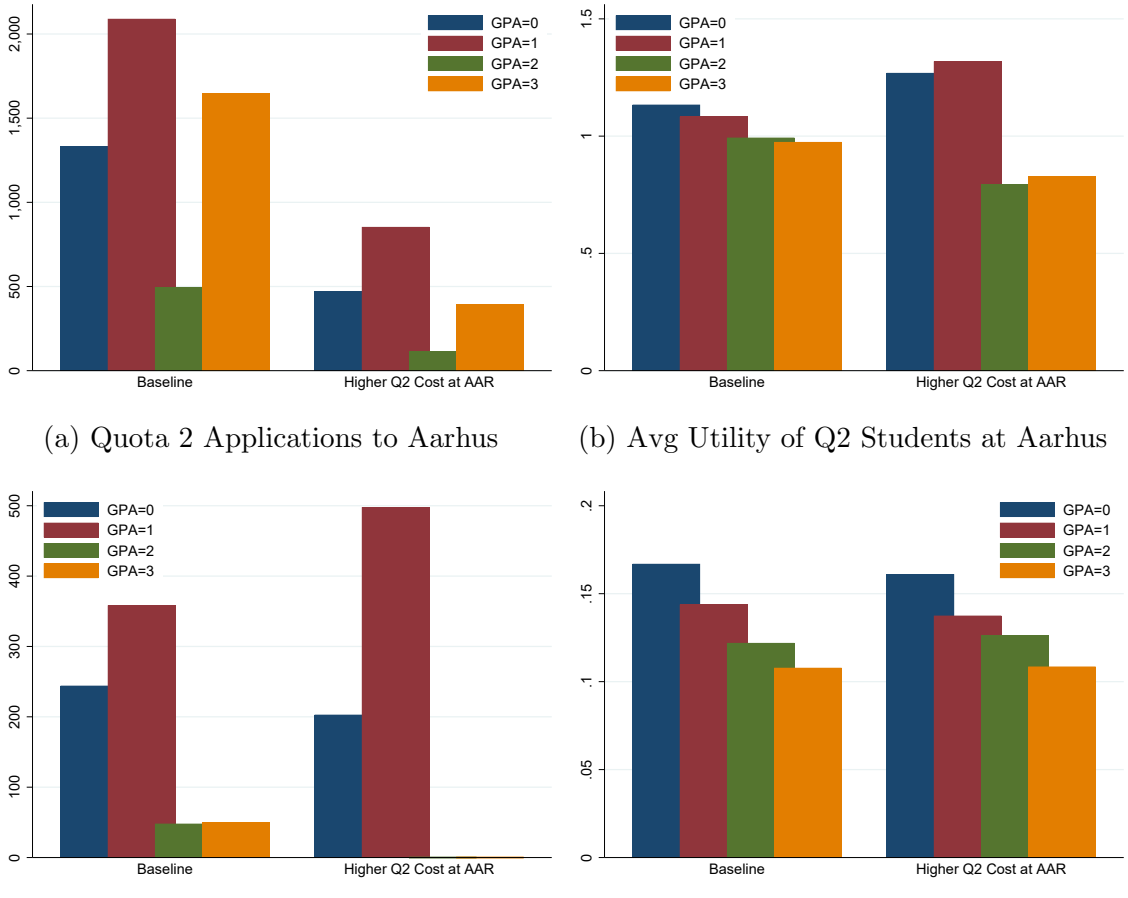
The estimates point to a program preference for non-locals. Odense tends to prefer students from Aarhus or other regions over Odense locals and Aarhus tends to prefer students from Odense or elsewhere over Aarhus locals. This points to program preference over student diversity, based on region of origin. 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 8. Figure 6 summarizes the effects on applications, enrollment, utility, and graduation at Aarhus by gpa in the first two panels of each figure.

Figure 6: 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

Table 9: 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.

Starting with Figure 6a, 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 6c. This effect may lower overall persistence rate at Aarhus as lower gpa students have lower completion rates on average, see the baseline estimates in Figure 6d. 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 6c.[23] Since preferences are positively correlated with talents, see again panel I in Table 8, this leads to an increase in persistence among lower gpa students as evidenced in Figure 6d.

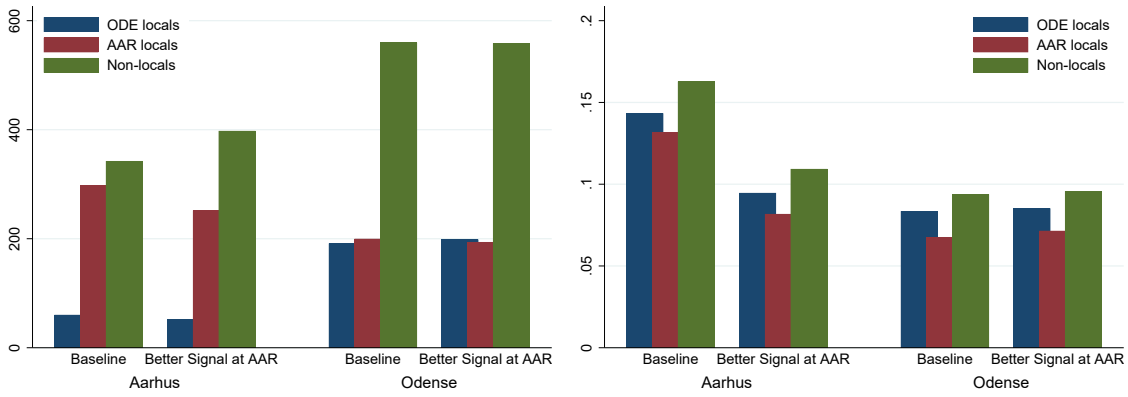
On net, we find a small increase in completion rates at Aarhus as indicated in Table 9. Focusing on the second column, we see an increase in Aarhus completion rate by 1.1 p.p. as we increase in quota 2 application costs. We find only minimal spillover effects on completion rates at Odense, see the first 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

[23]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.

8. Figure 7 summarizes the effects on enrollment, and graduation at Aarhus and Odense by student location in panels 1 and 3 of each figure.

Figure 7: Increasing Quota 2 Signal Precision at Aarhus



(a) Quota 2 Enrollment

(b) Quota 2 Dropout

Starting with Figure 7a, 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, 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 7b, 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 9. 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 9. 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.

References

Abdulkadiroğlu, Atila, Parag A Pathak, and Alvin E Roth (2005a). "The new york city high school match". *American Economic Review* 95.2, pp. 364–367.

Abdulkadiroğlu, Atila, Parag A Pathak, Alvin E Roth, and Tayfun Sönmez (2005b). "The Boston public school match". *American Economic Review* 95.2, pp. 368–371.

Agarwal, Nikhil (2015). "An empirical model of the medical match". *American Economic Review* 105.7, pp. 1939–78.

Arcidiacono, Peter and John Bailey Jones (2003). "Finite mixture distributions, sequential likelihood and the EM algorithm". *Econometrica* 71.3, pp. 933–946.

Arulampalam, Wiji, Robin A Naylor, and Jeremy P Smith (2007). "Dropping out of medical school in the UK: explaining the changes over ten years". *Medical Education* 41.4, pp. 385–394.

Avery, Christopher and Jonathan Levin (2010). "Early admissions at selective colleges". *American Economic Review* 100.5, pp. 2125–56.

Azevedo, Eduardo M and Jacob D Leshno (2016). "A supply and demand framework for two-sided matching markets". *Journal of Political Economy* 124.5, pp. 1235–1268.

Chade, Hector, Gregory Lewis, and Lones Smith (2014). "Student Portfolios and the College Admissions Problem". *The Review of Economic Studies* 81.3, pp. 971–1002.

Chakraborty, Archishman, Alessandro Citanna, and Michael Ostrovsky (2010). "Two-sided matching with interdependent values". *Journal of Economic Theory* 145.1, pp. 85–105.

Che, Yeon-Koo and Youngwoo Koh (2016). "Decentralized college admissions". *Journal of Political Economy* 124.5, pp. 1295–1338.

Cohen-Schotanus, Janke, Arno MM Muijtjens, Jan J Reinders, Jessica Agsteribbe, Herman JM Van Rossum, and Cees PM Van Der Vleuten (2006). "The predictive validity of grade point average scores in a partial lottery medical school admission system". *Medical Education* 40.10, pp. 1012–1019.

Compiani, Giovanni, Philip Haile, and Marcelo Sant'Anna (2020). "Common values, unobserved heterogeneity, and endogenous entry in US offshore oil lease auctions". *Journal of Political Economy* 128.10, pp. 3872–3912.

Daly, Moira and Daniel Le Maire (2019). *University admission and preferred field of study.* Tech. rep. Working Paper.

Duffy, Ryan D, R Stephen Manuel, Nicole J Borges, and Elizabeth M Bott (2011). "Calling, vocational development, and well being: A longitudinal study of medical students". *Journal of Vocational Behavior* 79.2, pp. 361–366.

Fox, Jeremy T, David H Hsu, and Chenyu Yang (2012). "Unobserved heterogeneity in matching games with an application to venture capital".

Friedrich, Benjamin (2020). "Internal labor markets and the competition for managerial talent". *Working Paper*.

Gale, David and Lloyd S Shapley (1962). "College admissions and the stability of marriage". *The American Mathematical Monthly* 69.1, pp. 9–15.

Hojat, Mohammadreza, Joseph S Gonnella, James B Erdmann, and J Jon Veloski (1996). "The fate of medical students with different levels of knowledge: Are the basic medical sciences relevant to physician competence?" *Advances in Health Sciences Education* 1.3, pp. 179–196.

Kawai, Kei, Ken Onishi, and Kosuke Uetake (2020). "Signaling in online credit markets". *Working Paper*.

Larroucau, Tomás and Ignacio Rios (2020). *Dynamic college admissions and the determinants of students' college retention*. Tech. rep. Technical Report 2020. and,"Do "Short-List" Students Report Truthfully.

Lee, Sam-Ho (2009). "Jumping the curse: Early contracting with private information in university admissions". *International Economic Review* 50.1, pp. 1–38.

Liu, Qingmin, George J Mailath, Andrew Postlewaite, and Larry Samuelson (2014). "Stable matching with incomplete information". *Econometrica* 82.2, pp. 541–587.

Liu, Rhianon, Joseph Carrese, Jorie Colbert-Getz, Gail Geller, and Robert Shochet (2015). ""Am I cut out for this?" understanding the experience of doubt among first-year medical students". *Medical teacher* 37.12, pp. 1083–1089.

Maher, Bridget M, Helen Hynes, Catherine Sweeney, Ali S Khashan, Margaret O'Rourke, Kieran Doran, Anne Harris, and Siun O'Flynn (2013). "Medical school attrition-beyond the statistics a ten year retrospective study". *BMC medical education* 13.1, pp. 1–16.

Milgrom, Paul R and Robert J Weber (1982). "A theory of auctions and competitive bidding". *Econometrica: Journal of the Econometric Society*, pp. 1089–1122.

Mørcke, Anne Mette, Lotte O'Neill, Inge Trads Kjeldsen, and Berit Eika (2012). "Selected determinants may account for dropout risks among medical students". *Dan Med J* 59.9, pp. 1–6.

Norman, Geoffrey R, Cees PM van der Vleuten, and David I Newble (2012). *International handbook of research in medical education*. Vol. 7. Springer Science & Business Media.

Nusche, Deborah (2016). *OECD reviews of school resources: Denmark 2016*. OECD.

O'Neill, Lotte Dyhrberg, Birgitta Wallstedt, Berit Eika, and Jan Hartvigsen (2011a). "Factors associated with dropout in medical education: a literature review". *Medical Education* 45.5, pp. 440–454.

O'Neill, Lotte, Jan Hartvigsen, Birgitta Wallstedt, Lars Korsholm, and Berit Eika (2011b). "Medical school dropout-testing at admission versus selection by highest grades as predictors". *Medical Education* 45.11, pp. 1111–1120.

Olejaz, Maria, Annegrete Juul Nielsen, Andreas Rudkjøbing, Hans Okkels Birk, Allan Krasnik, Cristina Hernandez-Quevedo, World Health Organization, et al. (2012). "Denmark: Health system review".

Roth, Alvin E (1982). "The economics of matching: Stability and incentives". *Mathematics of operations research* 7.4, pp. 617–628.

— (1989). "Two-sided matching with incomplete information about others' preferences". *Games and Economic Behavior* 1.2, pp. 191–209.

— (2008). "Deferred acceptance algorithms: History, theory, practice, and open questions". *international Journal of game Theory* 36.3, pp. 537–569.

Roth, Alvin E and Marilda Sotomayor (1992). "Two-sided matching". *Handbook of game theory with economic applications* 1, pp. 485–541.

Roth, Alvin E and Xiaolin Xing (1997). "Turnaround time and bottlenecks in market clearing: Decentralized matching in the market for clinical psychologists". *Journal of political Economy* 105.2, pp. 284–329.

Sönmez, Tayfun (1997). "Manipulation via capacities in two-sided matching markets". *Journal of Economic theory* 77.1, pp. 197–204.

Sørensen, Morten (2007). "How smart is smart money? A two-sided matching model of venture capital". *The Journal of Finance* 62.6, pp. 2725–2762.

Spence, Michael (1973). "Job market signaling". 88, pp. 355–374.

Stetto, Jayne E, Gary D Gackstetter, David F Cruess, and Tomoko I Hooper (2004). "Variables associated with attrition from uniformed services university of the health sciences medical school". *Military medicine* 169.2, pp. 102–107.

Strayhorn, Gregory (1999). "Participation in a premedical summer program for underrepresented-minority students as a predictor of academic performance in the first three years of medical school: two studies." *Academic medicine: journal of the Association of American Medical Colleges* 74.4, pp. 435–447.

Urlings-Strop, Louise C, Theo Stijnen, Axel PN Themmen, and Ted AW Splinter (2009). "Selection of medical students: a controlled experiment". *Medical Education* 43.2, pp. 175–183.

Ward, Alison M, Max Kamien, and Derrick G Lopez (2004). "Medical career choice and practice location: early factors predicting course completion, career choice and practice location". *Medical education* 38.3, pp. 239–248.

Yates, Janet (2012). "When did they leave, and why? A retrospective case study of attrition on the Nottingham undergraduate medical course". *BMC Medical Education* 12.1, pp. 1–7.

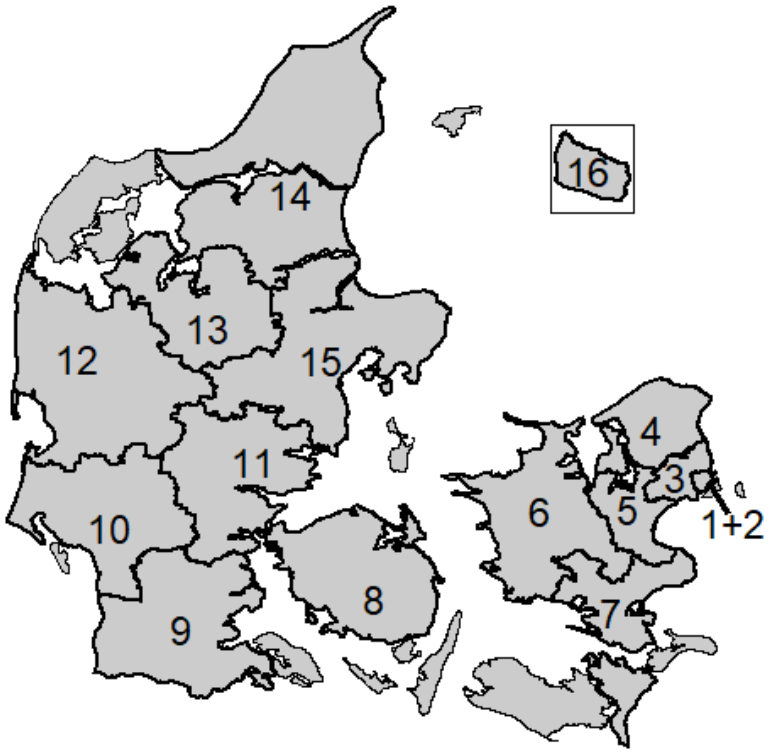
Yates, Janet and David James (2006). "Predicting the "strugglers": a case-control study of students at Nottingham University Medical School". *Bmj* 332.7548, pp. 1009–1013.

Appendix

A Data and Institutions

A.1 Danish Geography

Figure 8: 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

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

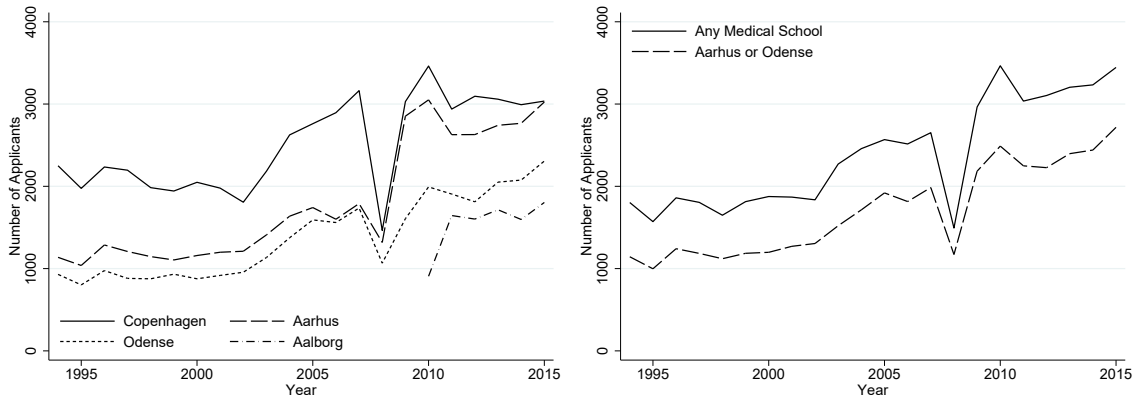
By Assumption 3, the term in parentheses is monotone increasing in ω_j, negative for sufficiently small ω_j, and positive for sufficiently large ω_j. The term $f(s_j|\omega_j)$ is a density and is (by assumption) always positive. Hence this expression crosses zero once from below as a function of ω_j.

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

C Additional Empirical Results

C.1 Details on Applicants

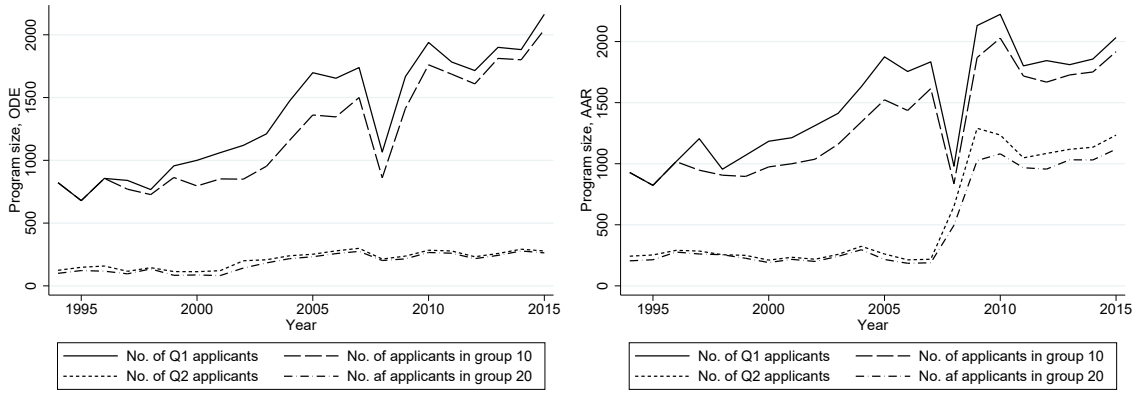
Figure 9: Applicants and Applications



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

Note: Figure 9a 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 9b 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.

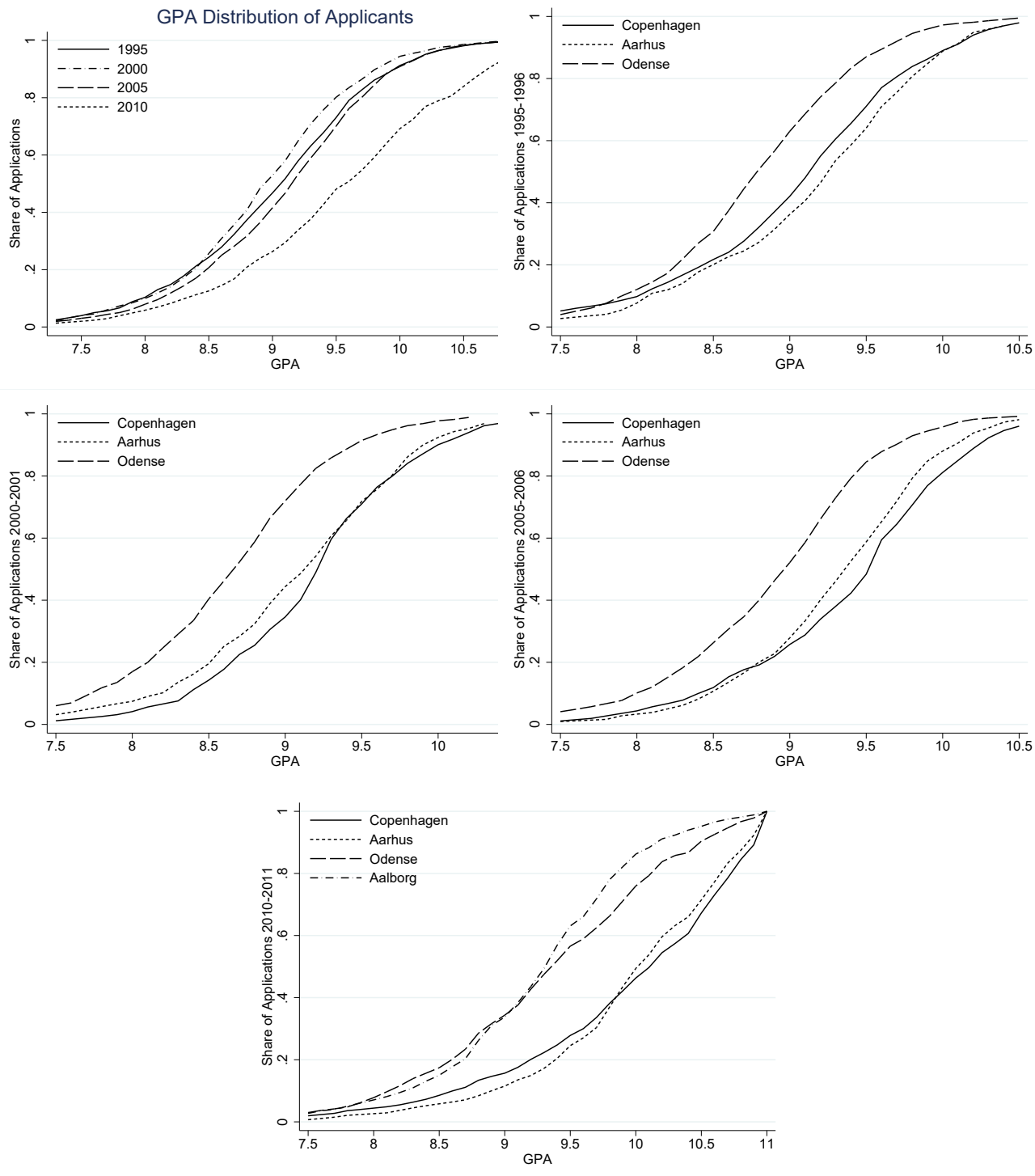
Figure 10: Applicants by Application Type



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

Note: Figures 10a and 10b 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 11: GPA Distribution of Medical School Applicants

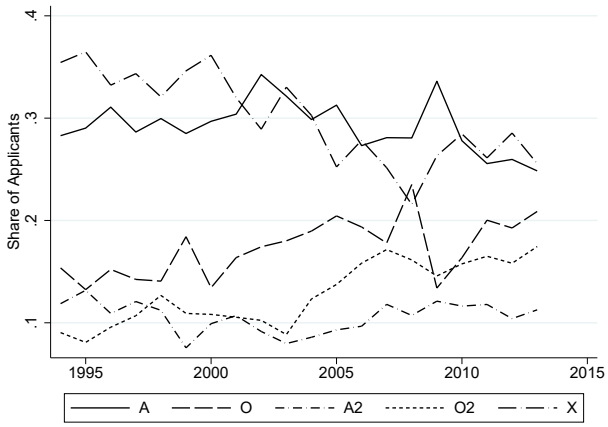


Note: The figure presents the high school GPA distribution for four different applicant groups, pooling two cohorts each. Each cohort includes applicants who indicate at least one of the four medical school programs in their submitted preference ranking. GPA is harmonized to the 7-point scale in all 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.[24] 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 12 and 13, respectively.

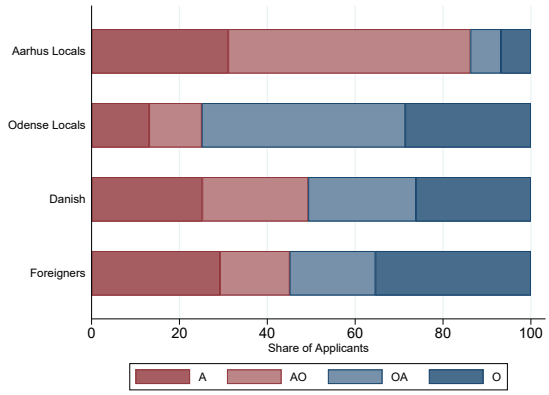
Figure 12: Program Preferences Over Time



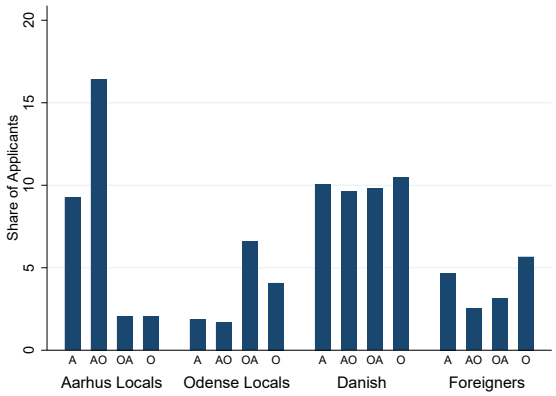
Note: To simplify the exposition, we group all applications based on the two medical programs listed with highest priority, irrespective of whether the applicant lists a third medical program or not. A denotes Aarhus, and O denotes Odense, X summarizes Copenhagen and Aalborg (available from 2010 onward).

[24] Counties near Aarhus include North Jutland, Aarhus, Vejle, Viborg, while counties near Odense include Funen, Storstrom, West Zealand, and South Jutland, see Appendix Figure 8 for a map. Figure 12 presents trends in the relative popularity of Aarhus and Odense over time.

Figure 13: 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 8.

C.2 Details on Admissions

Table 10: 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%	0.5%	0.7%	5.1%	2.0%
Copenhagen	Psychology	1.8%	1.4%	0.5%	0.0%	2.0%	0.0%
Aarhus	Psychology	1.9%	1.6%	0.3%	0.1%	2.9%	0.2%
Odense	Biomechanics	4.5%	3.3%	1.3%	1.3%	40.0%	15.8%
Aarhus	Dentistry	7.4%	5.7%	1.1%	0.6%	27.1%	5.5%
Copenhagen	Dentistry	8.4%	6.3%	2.2%	1.0%	22.9%	6.2%
Aalborg	Medical School	11.9%	8.8%	3.7%	0.2%	76.4%	11.1%
Copenhagen	Medical School	67.9%	19.8%	13.3%	0.6%	47.6%	0.8%
Aarhus	Medical School	70.3%	32.7%	25.9%	2.6%	61.2%	4.4%
Odense	Medical School	100.0%	0.0%	0.0%	0.0%	97%	0.0%
Sample		Applicants to Odense	Applicants to Odense	Applicants to Odense	Rejected at Odense	Applicants to Program j	Admitted to Program j

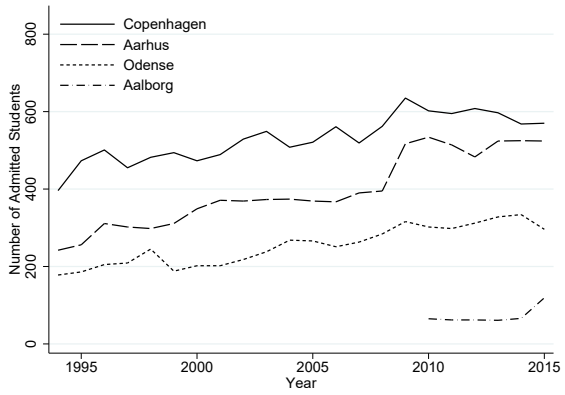
Note: This table presents summary statistics for applicants that apply to Odense's medical program. For cells with low case numbers we censor the share of the sample to zero to preserve confidentiality.

Capacity Figure 14a 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 9.

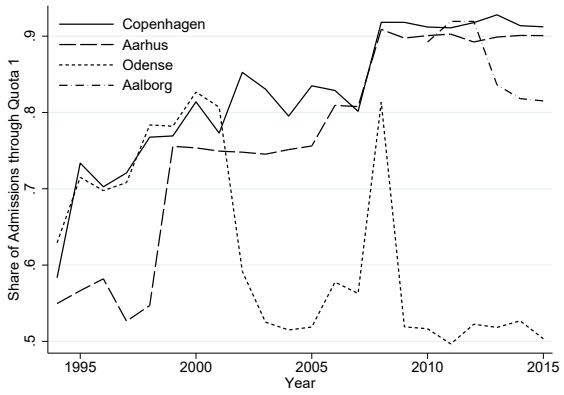
Quota 1 Admissions Figure 14b documents the share of quota 1 admissions out of all admissions by program and year. Figure 14e documents the quota 1 GPA cutoff, which is inversely related to the quota 1 share, holding the applicant pool fixed. To put the magnitude of the GPA cutoff into perspective, we present the distribution of high school GPA among medical school applicants in Appendix Figure 11.[25] 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

[25]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.

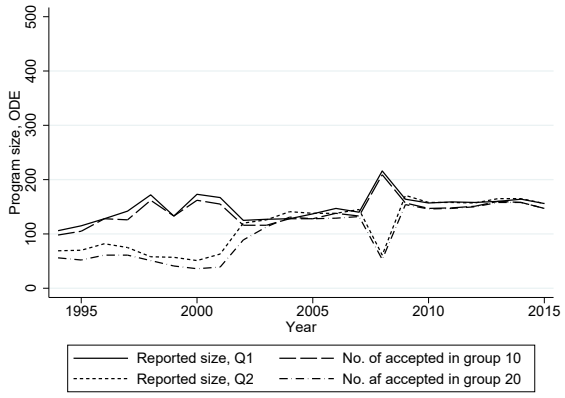
Figure 14: Admissions to Medical School Programs 1994-2013



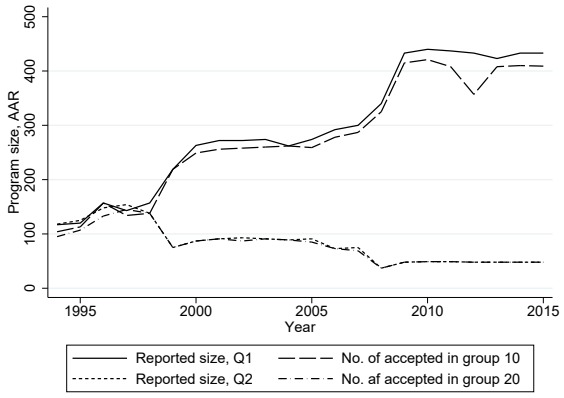
(a) Admissions to Medicine Programs



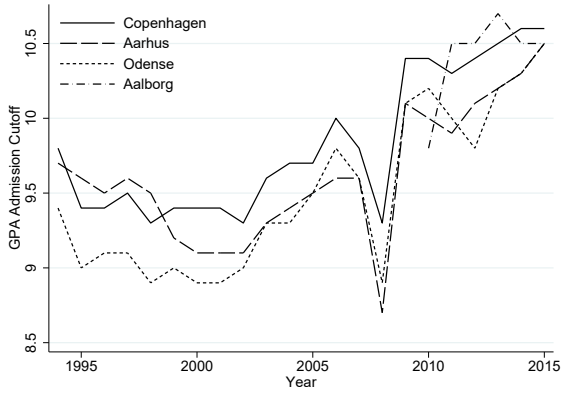
(b) Quota 1 Admission Share



(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 14a. Figure 14b documents the share of quota 1 admissions out of all admissions by program and year. Figures 14c and 14d 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 14e 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 14b 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

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

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

where we control for differential linear trends in gpa to the left and right of the GPA cutoff. The key parameter of interest is $\gamma_{screening}$, 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.

Robustness: We revisit these findings in various robustness exercises, which we summarize in Appendix Tables 11 and 12. We show that the discontinuity is robust to different treatment of measurement error in GPA, excluding standby admissions, and focusing on the early period 1994-2006. In addition, we compare the difference in dropout rates at the GPA threshold before and after the reform in Odense 2002. We find that Aarhus had more success in screening cases below the threshold in earlier years of the sample. Next, we consider the 1-year dropout rate as an alternative outcome measure. Here the difference in dropout rates at the GPA threshold equals 3.6 percentage points. 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 12. These students may be more

Table 11: Programs' Information Quality and Student Persistence

	(1) 1Y Dropout	(2) 1Y Med Dropout	(3) Completion	(4) Time to Complete
screening	-0.038***	-0.034***	0.086***	-46.504**
	(0.010)	(0.010)	(0.019)	(20.365)
gpa_q1	-0.001	-0.001	0.008***	-0.485
	(0.001)	(0.001)	(0.002)	(2.177)
gpa_q2	-0.001	-0.001	0.006*	-1.844
	(0.002)	(0.002)	(0.003)	(3.358)
Constant	0.084***	0.068***	0.796***	2,694.700***
	(0.013)	(0.013)	(0.022)	(24.024)
Observations	8,855	8,855	6,499	5,439
R-squared	0.007	0.006	0.009	0.073

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.

Table 12: 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
screening	-0.025**	-0.020*	-0.023	-0.015	0.062**	-32.881
	(0.012)	(0.012)	(0.020)	(0.019)	(0.026)	(27.930)
gpa_q1	-0.001	-0.001	-0.008**	-0.009***	0.020***	-7.481
	(0.002)	(0.002)	(0.004)	(0.003)	(0.006)	(6.726)
gpa_q2	-0.001	-0.001	-0.004*	-0.003	0.008***	-1.860
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(3.182)
Constant	0.048***	0.035**	0.138***	0.085***	0.846***	2,628.049***
	(0.018)	(0.018)	(0.031)	(0.029)	(0.036)	(38.441)
Observations	3,450	3,450	3,450	3,450	2,589	2,216
R-squared	0.007	0.008	0.017	0.015	0.015	0.090

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.

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 1.7 percentage points discontinuity at the GPA threshold, which becomes larger and statistically significant at Odense where we observe more quota 2 admissions.

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 Aarhus and Odense medical programs. We expand the analysis in Table 3 in the main text using alternative measures of student quality. Specifically, we summarize ranked applicants into quintiles 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 statistically significant 0.8 percentage point reduction in the three-year dropout rate. 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 1.3 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 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.

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

In this section, we conduct various robustness tests for the results in Table 4. First, we find a robust reduction in dropout rates when excluding standby admissions or excluding the year 2008, see Panel A of Table 16, columns 2 and 3. Complementing the results in column 5 of Table4, 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 15, column 4. These results hold similarly when excluding transfers from the dropout measure in columns 5-8.

Second, the effects are robust to including all medical schools in the sample rather than comparing Odense and Aarhus only, see Table 16. In addition, Table 15, Panel B shows robust results for alternative sample restrictions among students at all medical schools.

Figure 15 provides robustness for the results in Figure 3. While Figure 15a replicates the result on 3-year dropout rates at Odense from the main text, Figure 15b provides anal-

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

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Odense	Aarhus	Med Excl Odense	Non-Med	Not Odense
Panel A: Safe admission indicator					
better ranked	-0.035**	-0.025	-0.012	-0.102**	-0.059***
	(0.016)	(0.059)	(0.029)	(0.047)	(0.023)
R-squared	0.210	0.533	0.357	0.303	0.265
Panel B: Rank bins of 25 students each					
better ranked	-0.008**	-0.024*	-0.013**	-0.007	-0.014***
	(0.004)	(0.013)	(0.006)	(0.007)	(0.004)
R-squared	0.210	0.545	0.364	0.299	0.268
Panel C: Rank quintiles					
better ranked	-0.086***	-0.157*	-0.070	-0.121*	-0.121***
	(0.030)	(0.092)	(0.048)	(0.073)	(0.036)
R-squared	0.212	0.542	0.360	0.301	0.267
Observations	2,203	250	627	744	1,536

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

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Odense	Aarhus	Med Excl Aarhus	Non-Med	Not Aarhus
Panel A: Safe admission indicator					
better ranked	-0.031	0.022	-0.004	-0.016	-0.034*
	(0.050)	(0.028)	(0.032)	(0.028)	(0.020)
R-squared	0.306	0.202	0.225	0.112	0.096
Panel B: Rank bins of 25 students each					
better ranked	-0.004***	-0.004**	-0.002**	-0.002***	-0.002***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
R-squared	0.314	0.205	0.228	0.114	0.099
Panel C: Rank quintiles					
better ranked	-0.099**	-0.083*	-0.044	-0.076***	-0.093***
	(0.048)	(0.050)	(0.033)	(0.023)	(0.019)
R-squared	0.310	0.204	0.226	0.113	0.099
Observations	883	1,698	1,630	5,867	7,652

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

Note: Table 13 presents the effects of Odense's quota 2 ranking on different persistence measures, controlling for year by school fixed effects, resident location by school fixed effects, and year by GPA fixed effects. Panel A presents the effect of being ranked in the top, Panel B presents the effect of a higher quintile rank, and Panel C denotes the effect of being in a higher ranked bin of 25 students each. A higher quintile or rank means a higher position in the ranking. We consider the effects on the three-year dropout rate at Odense in columns 1, at Aarhus in column 2, medical school programs other than Odense in columns 3, non-medical school programs in columns 4, and any other program except Odense medical school in column 5. Table 14 is structured in the same way but shows the effect of Aarhus quota 2 ranking.

Table 15: Robustness: Odense's Dropout Rates and the Admission Reform

	(1) Prog 1y	(2) Prog 3y	(3) Med 1y	(4) Med 3y	(5) Completion	(6) Study Time
postode	-0.040***	-0.070***	-0.032***	-0.043***	0.037**	-117.647***
	(0.010)	(0.015)	(0.009)	(0.014)	(0.018)	(19.011)
Observations	18,575	18,575	18,575	18,575	13,652	11,385
R-squared	0.039	0.049	0.038	0.047	0.052	0.133

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

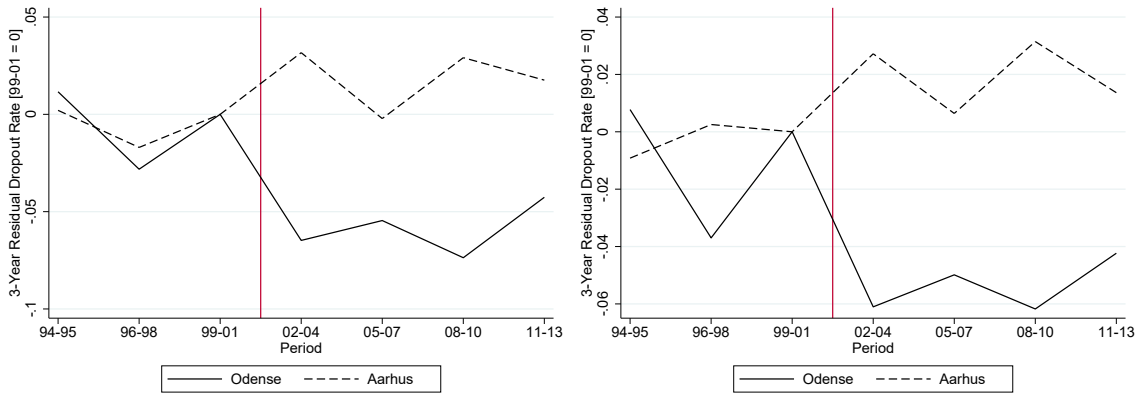
Table 16: Robustness: Odense's Dropout Rates and the Admission Reform

	(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	-0.071***	-0.067***	-0.069***	-0.085***	-0.047***	-0.042**	-0.044***	-0.060***
	(0.017)	(0.018)	(0.018)	(0.019)	(0.016)	(0.017)	(0.016)	(0.018)
Observations	10,497	9,781	9,921	7,714	10,497	9,781	9,921	7,714
R-squared	0.073	0.077	0.070	0.081	0.070	0.074	0.066	0.078
Panel B	Baseline	Excl Stby	Excl08	94-09	Baseline	Excl Stby	Excl08	94-09
postode	-0.070***	-0.063***	-0.069***	-0.081***	-0.043***	-0.035**	-0.043***	-0.054***
	(0.015)	(0.016)	(0.015)	(0.016)	(0.014)	(0.015)	(0.014)	(0.015)
Observations	18,575	17,073	17,573	13,652	18,575	17,073	17,573	13,652
R-squared	0.049	0.053	0.047	0.053	0.047	0.051	0.045	0.051

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

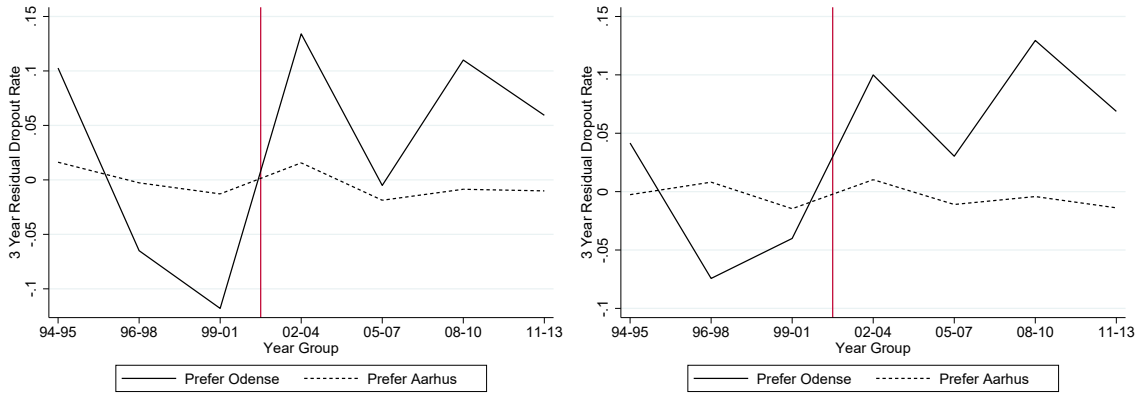
ogous results when excluding transfers. Figures 15c and 15d provide time series evidence complementing the pooled results in Figure 3b. Since the number of Aarhus students previously rejected at Odense fluctuates over time and is low in the early years of the sample, the patterns are less precise when 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 15d.

Figure 15: 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 15a and 15c plot the program-specific 3-year dropout rate of enrolled students over time, while Figure 15b and 15d 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 15c and 15d 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 15c reports the 3-year dropout rate while Figure 15d reports results for all dropouts, including transfers within the first three years.

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

Table17 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 17: Odense's Admission Reform and Performance of Students Admitted in Aarhus

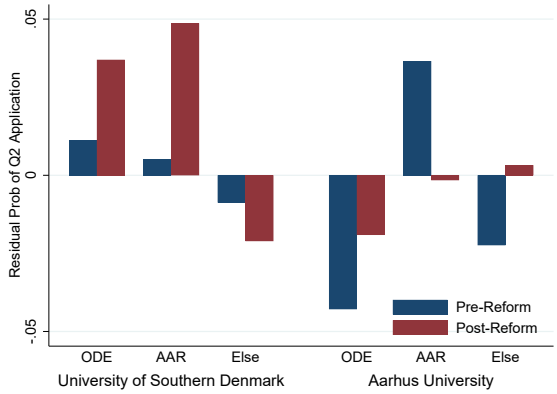
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	All	Ever Enrolled Med		Ever Enrolled AAR		Enrolled AAR	
	Full	1st obs	Full	1st obs	Full	1st obs	All	Excl Transfers
Prefer Odense	-0.040	-0.041	-0.031	-0.032	-0.031	-0.032	-0.031	-0.005
	(0.053)	(0.053)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.054)
Prefer Odense × Post	0.123**	0.126**	0.151**	0.161**	0.157**	0.166**	0.116*	0.076
	(0.058)	(0.059)	(0.063)	(0.064)	(0.063)	(0.065)	(0.066)	(0.063)
Constant	0.126***	0.126***	0.130***	0.130***	0.129***	0.129***	0.129***	0.118***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	7,487	7,148	6,803	6,484	6,746	6,430	6,333	6,333
R-squared	0.075	0.077	0.082	0.084	0.084	0.087	0.089	0.085

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

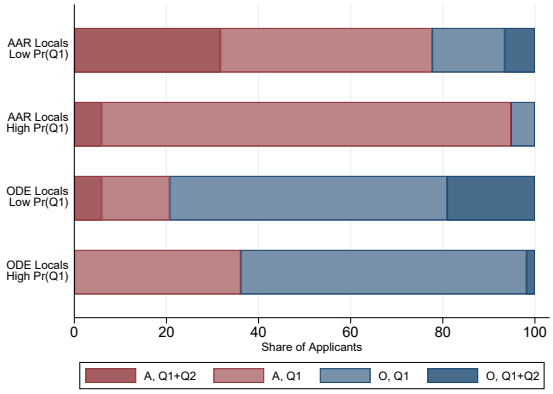
C.5 Details on Self-Selection and Quota 2 Admissions

Figure 16 provides additional evidence on the composition of quota 2 applicants, as well as the probability and composition of safe quota 2 admissions.

Figure 16: Quota 2 Applications and Admissions



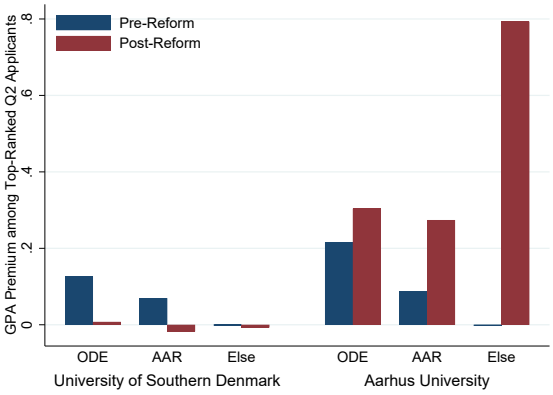
(a) Q2 Applications by Location



(b) Q2 Applications by Location and GPA



(c) Prob of Safe Admission

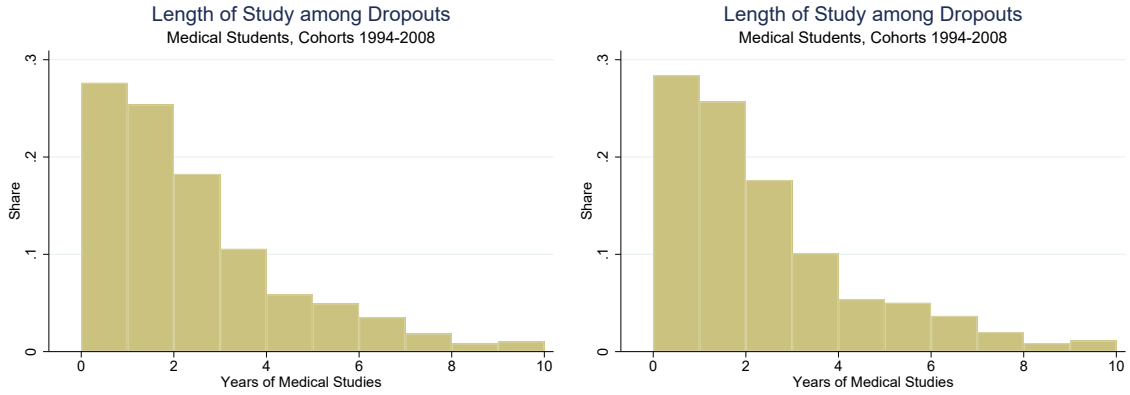


(d) GPA Premium among Safe Admissions

Note:.

C.6 Details on Dropouts

Figure 17: 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 17a and 17b document the distribution of study time until dropout among medical students who exit before graduation. Figure 17a defines exit as leaving the program, which includes transfers, while Figure 17b 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 18, 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 18 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 18: 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	90.20%	2.50%	7.40%
Copenhagen	72.70%	7.40%	19.90%
Aarhus	90.90%	3.30%	5.80%
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	36.60%	34.20%	29.20%
Copenhagen	70.40%	14.90%	14.70%
Aarhus	15.20%	61.30%	23.50%
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	80.70%	15.20%	4.20%
Copenhagen	69.60%	16.60%	13.80%
Aarhus	62.40%	20.40%	17.20%
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	45.90%	20.50%	
Copenhagen	4.80%	4.30%	
Aarhus	64.80%	11.80%	
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	2.7%	2.0%	
Copenhagen	1.2%	4.4%	
Aarhus	2.8%	3.2%	

To assess the overall attractiveness of rejection chains, we consider two benchmark scenarios in Panel E of Table 18. 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 $0.025 * 0.459 + 0.074 * 0.205 = 2.7\%$. 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 2.7% success rate is an upper bound. The analogous bounds for Aarhus and Copenhagen are 2.8% and 1.2%, respectively. Even though Copenhagen can place a 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 $0.025*0.342+0.074*0.152 = 2.0\%$. The analogous bounds for Aarhus and Copenhagen are 3.2% and 4.4%, respectively.

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

Table 19: 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

$$u_j \times \Big(Pr(j|\{j\}) - Pr(j|\emptyset) \Big) > c_{\{j\}}. \tag{25}$$

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

$$v_a = Pr(1|a) \times u_1 + Pr(2|a) \times u_2 - c_{\{a\}} \ , \tag{26}$$

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 $a' \neq a$.

E Details on the Estimation Procedure

As outlined in the main text, our estimation takes a sequential E-M following Arcidiacono and Jones (2003). To get starting values for parameters, we assume that talents follow a standard normal distribution . We discretize the support of talents into 9 levels defining grid into $K = 9 \cdot 9$ points and assign the probability mass to the respective points. To get starting values for parameters, we estimate equations (6), (12), (9) via probit and read off the parameters. We set the variance of quota 2 application costs to 1 and mean application costs to zero. We set the remaining parameters in the variance covariance matrix to zero. This provides us $\hat{p}^0 = (\hat{p}^0_1, ..., \hat{p}^0_K)$, and the structural parameters $\hat{\Theta}^0$. Building on these starting values, we iterate over the two M steps and the E step, which we now discuss in further detail.

E.1 M1 Step: Details

This step provides an estimate of the parameters $\Theta_1 = \{\alpha_j, \beta_{jt}, \rho_{jt}\}$. Given the conditional weights at any iteration l: $Pr[k|y_i, \hat{\Theta}^l, \hat{p}^l, x_i]$, this step reduces to simple probit regressions for dropouts and quota 2 admissions, which need to condition on talent.

For program j, we estimate that students persist (not drop out) iff

$$\lambda\tilde{\omega}_j + \lambda X\alpha_j + \tilde{\nu} > 0, \tag{27}$$

where $\tilde{\nu} \sim N(0,1)$. Here, λ denotes a scaling parameter that we set to $\lambda = \sqrt{10}$. An observation in this regression is person (i) type (k) combination. We thus conduct a weighted probit regression, weighted by the conditional weights $Pr[k|y_i, \hat{\Theta}^l, \hat{p}^l, x_i]$. Finally, we divide the probit coefficient by λ to arrive at an estimate for α_j.

Turning to quota 2 admissions, we estimate that a quota 2 applicant is admitted to program j iff

$$\frac{\rho_j}{\sqrt{1-\rho_j^2}}\tilde{\omega}_j - \frac{1}{\sqrt{1-\rho_j^2}}\underline{s}_j(X) + \frac{1}{\sqrt{1-\rho_j^2}}\tilde{s}_j > 0, \tag{28}$$

where the admission cutoff $\underline{s}_j(X)$ is defined in equation (12) and $\tilde{s}_j \sim N(0,1)$. In practice, for each j and time period $t \in \{pre, post\}$, we estimate a weighted probit, with ω_j and X as covariates, weighted by the conditional weights $Pr[k|y_i, \hat{\Theta}^l, \hat{p}^l, x_i]$. Let $\tilde{\beta}$ denote the

coefficients from this probit. The coefficient on $\tilde{\omega}_j$ is $\tilde{\beta}_{\omega_j} = \frac{\rho_j}{\sqrt{1-\rho_j^2}}$. Thus

$$\rho_j = \frac{\tilde{\beta}_{\omega_j}}{\sqrt{1+\tilde{\beta}_{\omega_j}^2}} \ . \tag{29}$$

Having obtained an estimate of ρ_j, we can rescale and update the rest of the parameters. This provides us with estimate for ρ_{jt} and β_{jt}.

E.2 M2 Step: Details

This step provides an estimate of the parameters $\Theta_2 = \{\gamma_j, \rho_{\epsilon j}, \delta_{jt}, \sigma_{ct}, \sigma_{c12t}\}$. To reduce computational complexity, we first characterize quota 1 and quota 2 application decisions conditional on preference shocks ϵ_u. In a second step, we integrate over the conditional distribution of talents of preferences shocks, conditional on talent $\tilde{\omega}$, to express quota 1 and quota 2 application decisions conditional on talent. Considering application decisions conditional on preference shocks first simplifies the calculation of likelihood of quota 2 application portfolios. Specifically, conditional on preference shocks, the first two summands of the quota 2 application payoff

$$v_a = Pr(1|a)u_1 + Pr(2|a)u_2 - c_a. \tag{30}$$

are constants and we only need to integrate over the distribution of application costs c_a, which are normally distributed, see (11).

In practice, we discretize the support of utility shocks into x levels defining an $x \times x$ grid of ϵ_u's, summing to a total of $M = x * x$ grid points. Let $Pr(\epsilon_u = \epsilon_u^{(m)})$ denote the probability that an applicant has preference shock $\epsilon_u^{(m)} = \epsilon_{u1}^{(m)}, \epsilon_{u2}^{(m)}$ for any utility grid point $m \in \{1, .., M\}$, with $\sum_m Pr(\epsilon_u = \epsilon_u^{(m)}) = 1$. Analogously, $Pr(\tilde{\omega} = \tilde{\omega}^{(k)})$ denotes the probability that an applicant has talent shock $\tilde{\omega}^{(k)} = \tilde{\omega}_1^{(k)}, \tilde{\omega}_2^{(k)}$ for any talent grid point $k \in \{1, .., K\}$.

Building on the utility grid, we start by characterizing the utility-type conditional likelihood of application decisions $h_m^2(y_i^2; \Theta_1, \Theta_2, x_i)$, which conditions on utility type m, as opposed to talent type k. More details on the calculation of h_m^2 are provided below. To calculate the *talent-type* conditional likelihood of application decisions, we integrate over the conditional distribution of $\epsilon_u|\tilde{\omega}$. Specifically, we calculate:

$$h_k^2(y_i^2; \Theta_1, \Theta_2, x_i) = \sum_{m=1}^{M} h_m^2(y_i^2; \Theta_1, \Theta_2, x_i) \cdot Pr(\epsilon_u = \epsilon_u^{(m)}|\tilde{\omega} = \tilde{\omega}^{(k)})$$

where $Pr(\epsilon_u = \epsilon_u^{(m)}|\tilde{\omega} = \tilde{\omega}^{(k)})$ is the conditional probability of having being of utility

type m conditional on being of talent type k. This conditional probability is known up to parameters, as indicated in equation (10).

E.2.1 Preferences and Applications:

$h_m^2(y_i^2; \Theta_1, \Theta_2, x_i)$ describes the probability of the observed quota 1 applications, the preference ranking , and the quota 2 portfolio, conditional on utility shock m. Specifically, y_i^2 includes the three sets of outcomes that we now discuss in more detail.

Quota 1 applications: As outlined in the main text, students apply to a program j via quota 1 iff $u_j \geq 0$. Conditional on preference shocks, u_j is deterministic. Let let $h_m^{2,1j}(y_i^2; \Theta_1, \Theta_2, x_i)$ denote this partial conditional likelihood of applying to quota 1 at program j and let $q1_{ij}$ denote an indicator that turns on if person i applied to j. Then we have $h_m^{2,1j}(y_i^2; \Theta_1, \Theta_2, x_i) = \mathbb{1}\{(q1_{ij} = 1 \cap u_j \geq 0) \cup (q1_{ij} = 0 \cap u_j < 0)\}$.

Preference ranking: Students prefer program j over j' iff $u_j \geq u_j'$. Let $h_m^{2,2}(y_i^2; \Theta_1, \Theta_2, x_i)$ denote the partial conditional likelihood of ranking program Odense over Aarhus and let $\succ_i^{ODE}$ denote an indicator that turns on if person i prefers Odense. Then we have $h_m^{2,2}(y_i^2; \Theta_1, \Theta_2, x_i) = \mathbb{1}\{(\succ_i^{ODE} = 1 \cap u_{ODE} \geq u_{AAR}) \cup (\succ_i^{ODE} = 0 \cap u_{ODE} < u_{AAR})\}$.

Quota 2 applications: As an intermediate step to characterize the optimal quota 2 application decisions, we need to specify the admission chances, conditional on utility shocks. Going in reverse order to the previous discussion, we first calculate the admission chances, conditional on talents, and then integrate over the distribution of talents, conditional on preference shocks. For example, we calculate the conditional probability of being admitted via quota 2 to program j as follows:

$$F_{s_j|\epsilon^u}(\underline{s}_j(x)|\epsilon^u) = \int F_{s_j|\tilde{\omega}}(\underline{s}_j(x)|\tilde{\omega}) dPr(\tilde{\omega}|\epsilon^u) \ .$$

We calculate $F_{s_j|\tilde{\omega}}(\underline{s}_j(x)|\tilde{\omega})$ using the parameters recovered from step M1 leveraging the distributional assumption imposed in equation 7. To characterize $Pr(\tilde{\omega}|\epsilon^u)$, we use Bayes rule and rewrite the expression to:

$$Pr(\tilde{\omega}|\epsilon^u) = \frac{Pr(\epsilon^u|\tilde{\omega}) \cdot Pr(\tilde{\omega})}{Pr(\epsilon^u)} \ .$$

Conditional on current parameter guesses, $Pr(\epsilon^u|\tilde{\omega})$ is known, as discussed above, and so is $Pr(\tilde{\omega} = \tilde{\omega}^{(k)}) = p_k$. Combined, this provides us with an estimate of $Pr(\tilde{\omega} = \tilde{\omega}^{(k)}, \epsilon^u = \epsilon^{(m)})$. Finally, we estimate $Pr(\epsilon^u)$ by:

$$Pr(\epsilon^u = \epsilon^{(m)}) = \sum_{k=1}^{K} Pr(\tilde{\omega} = \tilde{\omega}^{(k)}, \epsilon^u = \epsilon^{(m)}) \ .$$

With the quota 2 admission chances at hand, we calculate the first two summands of (30). The likelihood of observing a specific quota 2 application portfolio is then the probability that the multivariate normal distribution over application cost shocks and their difference, $(c_1, c_2, c1 - c2)$, falls in right rectangular prism. We refer to this conditional likelihood as $h_m^{2,3}(y_i^2; \Theta_1, \Theta_2, x_i)$. Finally, we have

$$h_m^2(y_i^2; \Theta_1, \Theta_2, x_i) = \Pi_{j=1}^2 \Big(h_m^{2,1j}(y_i^2; \Theta_1, \Theta_2, x_i) \Big) \cdot h_m^{2,2}(y_i^2; \Theta_1, \Theta_2, x_i) \cdot h_m^{2,3}(y_i^2; \Theta_1, \Theta_2, x_i) \ .$$

E.3 Non-Graduation Preferences

Table 20: Non-Graduation Preferences

Location	GPA	Post	Persistence Marginal Student		Non-Graduation Preferences: $\pi(x)$	
			Odense	Aarhus	Odense	Aarhus
Else	0	FALSE	0.866719	0.793799	-0.02267	0.085192
Else	0	TRUE	0.847038	0.811903	0.016686	0.076068
Else	1	FALSE	0.860269	0.815927	-0.01622	0.063064
Else	1	TRUE	0.851089	0.838792	0.012635	0.049179
Else	2	FALSE	0.873096	0.83322	-0.02905	0.045771
Else	2	TRUE	0.867179	0.864366	-0.00345	0.023605
Else	3	FALSE	0.891972	0.857874	-0.04792	0.021117
Else	3	TRUE	0.879951	0.881921	-0.01623	0.00605
Odense	0	FALSE	0.860052	0.789373	-0.016	0.089618
Odense	0	TRUE	0.868274	0.828944	-0.00455	0.059027
Odense	1	FALSE	0.85013	0.830674	-0.00608	0.048316
Odense	1	TRUE	0.861453	0.869246	0.002271	0.018725
Odense	2	FALSE	0.844047	0.856009	0	0.022982
Odense	2	TRUE	0.863725	0.902767	0	-0.0148
Odense	3	FALSE	0.869469	0.892997	-0.02542	-0.01401
Odense	3	TRUE	0.867491	0.919358	-0.00377	-0.03139
Aarhus	0	FALSE	0.933148	0.848392	-0.0891	0.030599
Aarhus	0	TRUE	0.903379	0.851451	-0.03965	0.03652
Aarhus	1	FALSE	0.90464	0.864548	-0.06059	0.014443
Aarhus	1	TRUE	0.857335	0.871396	0.006389	0.016575
Aarhus	2	FALSE	0.903715	0.878991	-0.05967	0
Aarhus	2	TRUE	0.816362	0.887971	0.047362	0
Aarhus	3	FALSE	0.911603	0.891408	-0.06756	-0.01242
Aarhus	3	TRUE	0.783067	0.899712	0.080657	-0.01174

F Inference

We estimate standard errors by rewriting the optimization as a GMM problem. We have the following four moment conditions

$$E_{y,x}\begin{pmatrix} \sum_{k=1}^{K} Pr[k|y,\Theta^*,p^*,x]\cdot\frac{\partial ln(h_k^1(y^1;\Theta_1^*,x))}{\partial\Theta_1} \\ \sum_{k=1}^{K} Pr[k|y,\Theta^*,p^*,x]\cdot\frac{\partial ln(\cdot h_k^2(y^2;\Theta_1^*,\Theta_2^*,x))}{\partial\Theta_2} \\ Pr[1|y,\Theta^*,p^*,x]-p_1^* \\ . \\ . \\ . \\ Pr[K|y,\Theta^*,p^*,x]-p_K^* \end{pmatrix}=0\ . \tag{31}$$

We define the sample analogues as

$$G(\Theta^*)=\frac{1}{N}\sum_{i=1}^{N}\begin{pmatrix} \sum_{k=1}^{K} Pr[k|y_i,\Theta^*,p^*,x_i]\cdot\frac{\partial ln(h_k^1(y_i^1;\Theta_1^*,x_i))}{\partial\Theta_1} \\ \sum_{k=1}^{K} Pr[k|y_i,\Theta^*,p^*,x_i]\cdot\frac{\partial ln(\cdot h_k^2(y_i^2;\Theta_1^*,\Theta_2^*,x_i))}{\partial\Theta_2} \\ Pr[1|y_i,\Theta^*,p^*,x_i]-p_1^* \\ . \\ . \\ . \\ Pr[K|y_i,\Theta^*,p^*,x_i]-p_K^* \end{pmatrix}=0\ . \tag{32}$$

and let

$$g_i(\Theta^*)=\begin{pmatrix} \sum_{k=1}^{K} Pr[k|y_i,\Theta^*,p^*,x_i]\cdot\frac{\partial ln(h_k^1(y_i^1;\Theta_1^*,x_i))}{\partial\Theta_1} \\ \sum_{k=1}^{K} Pr[k|y_i,\Theta^*,p^*,x_i]\cdot\frac{\partial ln(\cdot h_k^2(y_i^2;\Theta_1^*,\Theta_2^*,x_i))}{\partial\Theta_2} \\ Pr[1|y_i,\Theta^*,p^*,x_i]-p_1^* \\ . \\ . \\ . \\ Pr[K|y_i,\Theta^*,p^*,x_i]-p_K^* \end{pmatrix}\ . \tag{33}$$

We define

$$V_0(\Theta)=\frac{1}{N}\sum_i g_i(\Theta)'g_i(\Theta)\ . \tag{34}$$

Finally, the variance covariance matrix is given by:

$$VCOV=\frac{1}{N}\cdot B_0^{-1}\Omega^0 B_0^{-1} \tag{35}$$

where

$$B_0 \;=\; \Gamma_0'\Gamma_0 \tag{36}$$

$$\Gamma_0 = \frac{1}{N}\sum_i \frac{g_i(\Theta^*)}{\partial\Theta'} \tag{37}$$

$$\Omega_0 = \Gamma_0' V_0 \Gamma_0 \tag{38}$$

Notes:

- For $\Gamma_0 = \frac{1}{N}\sum_i \frac{g_i(\Theta^*)}{\partial\Theta'}$, we need to take the derivative over $f(\cdot)$ **AND** $Pr[k|y_i, \Theta^*, p^*, x_i]$. For example, when considering the first argument in g_i, $g_i^1 = \sum_k Pr[k|y_i, \Theta^*, p^*, x_i] \cdot \frac{\partial ln(h_k^1(y_i^1;\Theta_1^*;x_i))}{\partial\Theta_1}$ we have

$$\frac{\partial g_i^1}{\partial\Theta'} = \sum_{mn} \frac{\partial Pr[k|y_i, \Theta^*, p^*, x_i]}{\partial\Theta'} \cdot \frac{\partial ln(h_k^1(y_i^1;\Theta_1^*;x_i)}{\partial\Theta_1} \tag{39}$$

$$+ \sum_{mn} Pr[k|y_i, \Theta^*, p^*, x_i] \cdot \frac{\partial^2 ln(h_k^1(y_i^1;\Theta_1^*;x_i)}{\partial\Theta_1\partial\Theta'} \tag{40}$$

- Need to divide by N in $VCOV = \frac{1}{N} \cdot B_0^{-1}\Omega^0 B_0^{-1}$ to reflect sample size
- Γ_0 is not symmetric