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[‖]

March 28, 2024

Abstract

This paper presents the first empirical evidence of interdependent values and strategic responses by market participants in a two-sided matching market. We consider the market for medical school programs in Denmark, which uses a centralized assignment mechanism. Leveraging unique administrative data and an information experiment, we show that students and rival programs hold payoff-relevant information that each program could use to admit students with higher persistence rates. Programs respond to these two sources of interdependent values, student self-selection and interdependent program values, by exhibiting ”home bias” towards local applicants. We construct and estimate a novel equilibrium model reflecting this evidence, and find that fully sharing information could significantly increase student persistence and program payoffs, but enabling students to communicate first preferences would leave outcomes unchanged. An alternative model assuming independent private values contradicts the empirical evidence, highlighting the importance of accounting for interdependent values in understanding and designing matching markets.

*We thank seminar participants at Berkeley, Chicago, Georgetown, Gothenburg, Helsinki, Imperial College London, Maryland, Michigan, Microsoft Research, MIT, Northwestern, Penn, Princeton, Stanford, Toulouse, UCLA, UNC, UT Austin, Washington University, and conference participants at NBER IO 2021, RIDGE IO 2021, $(IO)^2$, DSE 2022 at MIT, and SOLE 2022. We thank Nikhil Agarwal, Clemence Idoux, Tomas Larroucau, Parag Pathak, and Paulo Somaini for their helpful comments and discussions. We thank the Department of Economics and Business, Aarhus University, and VIVE Denmark for their invaluable support and for making the data available. IRB review was provided by the UCLA Institutional Review Board under reference number #23-001628.

[†]Northwestern University, Kellogg School of Management
[‡]UCLA, Department of Economics, CESifo, and NBER
[§]Princeton University & NBER
[¶]Princeton University
[‖]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, depends 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 learns about the ability and motivation of a prospective student through interviews and recommendation letters, which may leave 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 and perhaps its admission decision. When this is the case—that is, when the students' and rival programs' private information is relevant to programs' payoffs—we say that the information structure exhibits interdependent values.

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 first leverage unique administrative data and an information experiment to investigate two sources of interdependent values: interdependent program values and student self-selection on unobserved preferences. Second, consistent with this evidence, we construct and estimate a novel equilibrium model of a two-sided matching market with interdependent values and simulate counterfactuals to quantify the impacts of interdependent values and simulate alternative mechanisms in our setting.

We first show that interdependent program values and student self-selection are both present, and that programs respond strategically by exhibiting a "home bias" in favor of local applicants. Our counterfactuals then show that these forces matter for programs' payoffs and students' outcomes. Relative to a benchmark in which all parties' information is shared, the present situation involves substantially lower program payoffs and higher dropout rates. However, improving the market design while respecting agents' incentives is hard. Although students could in principle benefit from credibly communicating that they prefer a program, eliciting such preferences would induce strategic incentives. Consequently, policies that change application costs or reveal first-preference applications to programs in equilibrium would not lead to a significant improvement in persistence rates. Finally, we show that accounting for imperfect information matters as well. An alternative model with private values fails to match key patterns in the data and would have reversed the signs of the impacts of policy interventions.

To reach these conclusions, we exploit the following features of our setting. First, Danish medical programs have non-completion rates of up to 17% conditional on enrollment, in addition to the approximately 15% of students who renege on their offers. Thus, although we consider elite programs attracting the strongest high-school graduates, there is variation in student persistence, which we take as an outcome of interest. Moreover, improving the market design can have nontrivial impacts on the production of doctors.

Second, we have rich administrative data on the universe of program applications, admissions, and study outcomes. Matching takes place via a centralized deferred acceptance procedure. We observe student preference rankings over programs, and program rankings over students in a discretionary setting, that are submitted to the mechanism. In addition, we observe students' downstream outcomes including student enrollment and dropout. We are not aware of a different setting that provides information on all of these variables.

Third, we are able to exploit institutional features to test for and quantify imperfect information and interdependent values. Specifically, student admissions are split into two categories: quota 1 and quota 2. Quota 1 admissions are determined exclusively by students' high school GPA, a variable commonly observed by all players in the market and by researchers. In contrast, quota 2 candidates submit additional materials, such as letters of motivation and personal interviews. If these students do not gain admission via quota 1, they may be chosen for quota 2 seats based on the program's evaluation of these inputs. An implication is that admitted students with GPAs just below the minimum GPA for quota 1 admission are positively selected on the program's perceptions, while those just above are not. Moreover, because it is costly to write essays and sit for interviews and exams, the decision to submit a quota 2 application may reveal information held by students.

Fourth, we exploit a targeted information experiment that introduced changes to the requirements for quota 2 applications at one program, affecting that program's ability to screen, and applicants' incentives to submit quota 2 applications. By analyzing admissions from both quota 1 and quota 2, together with this experiment, we are able to distinguish the program's screening of applicants from the students' self-selection into the applicant pool.

Our analysis proceeds as follows. We begin by presenting descriptive facts, showing that programs have some but not complete information on students' potential dropout outcomes and that they act on this in their admission decisions. Using a regression discontinuity design, we show that students admitted via quota 2 have significantly lower dropout rates than their peers admitted via quota 1. This difference can partly be explained by better program screening of quota 2 students: Among quota 2 admissions, students who are ranked higher by the program have lower dropout rates. We also find evidence of advantageous self-selection among quota 2 applicants; within the quota 1 admissions—based solely on GPA—we find that students who also applied via quota 2 have lower dropout rates than their peers who did not.

We then turn to an 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 rival programs, we find that the reform led to a substantial decrease in Odense's dropout rate. In contrast, the reform led to an adverse selection of students at its closest competitor, Aarhus. We document a substantial increase in dropout rates at Aarhus among students who prefer Odense but are admitted to Aarhus in the post-reform period.

These findings are consistent with interdependent program values, i.e. a greater winner's curse at Aarhus when Odense increases its screening precision so that rejection by Odense is worse news. To investigate interdependent program values, we examine programs' rankings of quota 2 applicants. Conditional on Aarhus' ranking of one candidate relative to another, a better ranking by Odense predicts a lower dropout rate, in particular in the post-reform period. The reform effects are also consistent with changes in student self-selection, however, if the revised review process increased the application costs borne by students. If so, less motivated students may apply via quota 2 to Aarhus instead of Odense, potentially contributing to the dropout patterns when preferences are correlated with dropout outcomes.

Finally, we investigate programs' strategic responses to interdependent values. When students' preferences correlate with academic success, programs may attempt to prioritize students who rank them highly. Doing so may also mitigate the winner's curse. A student is not subject to a winner's curse at their first-choice program, but has received a rejection in the event they enroll at a lower choice. Hence students who prefer a rival program are more likely to be adversely selected if the rival program holds payoff-relevant information. These strategic incentives are muted when the program's own signal becomes more informative. Conversely, when rejection decisions by a rival program become more informative, programs may have greater incentives to favor students who prefer them over the rival program.

While programs cannot condition their decisions on the student's preference rankings, they may condition on factors related to applicants' geographical area of residence, which we show is a strong predictor of the student's preference ranking. We find some evidence consistent with strategic responses to interdependent values. Both Odense and Aarhus favor locals in their admissions in the pre-reform period. Odense weakens its bias towards locals in the post-reform period as it becomes better at screening applicants. Aarhus instead increasingly favors foreign applicants.

Building on these observations, we develop an estimable empirical model of this two-sided matching market with interdependent values. This model allows us to quantify the impacts of student self-selection and interdependent program values, the potential gains from resolving information frictions, and the impacts of 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 correlation 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 formally characterize admission and application decisions in this setting when matches are formed based on a program-proposing deferred acceptance mechanism (DA). We develop sufficient conditions for admission decisions to be governed by cutoff policies and characterize the cutoff rule.

We then estimate a parameterized version of the model via the generalized method of moments (GMM). We use data from before and after the reform, allowing student preferences, 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 the parameters of the dropout process fixed.

The estimated model fits the targeted patterns of application behavior, admissions, and outcomes by program and period well. The model estimates also indicate that applicants prefer and are more likely to persist in local programs, conditional on GPA. Foreigners are less likely to persist. Programs respond to preferences and talents by favoring local applicants in their quota 2 admission rules. We also find that quota 2 applications are costly from the point of view of students, particularly so for Odense in the post-reform period. This provides students with an instrument for market signaling in the spirit of Spence (1973). In addition, we show that our model matches key untargeted moments, such as the discontinuity in persistence at the GPA admission threshold for quota 1, the advantageous selection of quota 2 applicants, the screening precision of programs among quota 2 applicants, and the informativeness of rival screening, as well as the impacts of the information experiment on Odense and its closest rival, Aarhus. This stands in contrast to the performance of an alternative model with independent private values that we estimate for comparison. The latter rules out any role for self-selection and rival screening, and instead overstates the importance of own-program screening.

Finally, we conduct counterfactual analyses to assess the importance of information frictions while allowing for strategic responses of market participants to changes in the information structure. To quantify the total cost of information frictions for student outcomes, we analyze a scenario with free applications where all signals and preferences are commonly observed. Our results suggest that the efficiency gains from full information are large, ranging from 7 p.p. at Odense to 22 p.p. at Aarhus. Yet, realizing part of these potential gains through market design is difficult. We consider a scenario in which programs observe and can condition their decisions on the student's first preference in their quota 2 admissions. While this may provide a means for preference signaling, we find that the strategic application behavior of lower-potential applicants renders the intervention largely ineffective.

Our analysis is connected to several strands of 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. Centralized stable matching mechanisms have appealing properties when agents on both sides know their own preferences (Gale and Shapley, 1962; Roth and Sotomayor, 1992; Roth, 2008), even if students are uncertain about what colleges want (Roth, 1989). Methodologically, we build on cutoff representations of matchings (Azevedo and Leshno, 2016) as well as on tools from auction theory (Milgrom and Weber, 1982), and from empirical studies of interdependent-value auctions (Compiani et al., 2020) with asymmetric bidders (Somaini, 2020). As in Somaini (2020), agents' location provides information about their preferences.

Empirical work in two-sided matching markets typically uses stability as a solution concept, and assumes that agents know their own preferences (Sørensen, 2007; Fox et al., 2018; Agarwal, 2015). 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 program-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. The key novel feature of our model is the information structure of interdependent values. We provide sufficient conditions that ensure that a program's optimal admission rule is a cutoff policy in its private signal which varies by observable applicant characteristics, including a public signal of applicants' private preferences (location). We then estimate this cutoff function in our data.

Second, we contribute to the literature on matching markets with imperfect information. 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. 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 (2023) studies the role of imperfect information on matching between managers and firms. Firms intensify competition for promising young talent and increasingly use internal training and promotions to avoid adverse selection when hiring managers externally. Board et al. (2017) study a competitive labor market and show theoretically that firms with superior screening abilities post higher wages, attract and hire better applicants, and impose a compositional externality on low-wage firms leading to equilibrium inefficiency. 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 allow students 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 who 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 program 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, our analysis sheds new light on the market design tradeoffs inherent to the assignment of students to programs, a process that follows different protocols across countries. We add to a recent and growing literature on how changes in admission criteria affect student applications and admissions (Idoux, 2022; Kapor, 2020; Gandil and Leuven, 2022; Bjerre-Nielsen and Chrisander, 2022; Borghesan, 2022).

[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 Institutional Background

We focus our empirical analysis on medical school programs in Denmark. Medical school is a six-year program and candidates may apply immediately after completing their high school education. After completing their final exams, medical doctors must complete one year of clinical basic education, followed by specialist (including general practitioner) training for five to six years (see Olejaz et al. (2012), for details). Below we discuss the admission process to medical school programs in further detail, before describing the data collection.

2.1 University Applications and Admissions

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

Each program has a fixed capacity of seats. These seats are divided into two categories, quota 1 and quota 2, that have distinct admission criteria. Quota 1 seats are allocated purely on the grounds of the applicants' high-school GPA. Quota 2 seats are granted to applicants who do not meet the GPA requirements, and are allocated based on a broader set of characteristics, including the program's assessment of the applicant's cognitive skills, motivation and past experience.

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

During our sample period, the number of seats in medicine programs was determined by a government agency to meet the future public demand for healthcare professionals. Programs determine the fraction of college seats that are assigned to quota 1 and quota 2 in March-April, subject to national higher education regulations, which we return to below.[2]

[2] In 2001 the regulation decreased the share of quota 2 seats to a maximum of 25% of capacity, and in 2008 it was further reduced to 10%. Medicine programs typically also maintain a smaller quota 1 standby list. This list assigns vacated seats, as some students decide not to enroll, to the next best applicants who indicated a preference for standby seats in their application. The standby 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

2.2 Rankings and the Deferred Acceptance Algorithm

Quota 2 applications are due in mid-March and quota 1 applications are due in early July. The quota 1 application consists of an ordinal ranking of the student's (up to) 8 most preferred programs. When a student submits a quota 2 application to a program, CAS automatically considers the student for admission via quota 1 as well. However, it is possible to submit a quota 1 application to a program without a quota 2 application. In total, a student can apply to at most 8 distinct programs and submit a total of up to $8 + 8 = 16$ program-by-quota student applications if the student has applied to all 8 programs via quota 2 as well. In our setting, 99% of applicants list 7 or fewer distinct programs in total.

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

Programs rank student applicants within each quota. Quota 1 applicants are ranked passively based on their GPA. Programs choose a ranking of their quota 2 applicants. To do so, programs assign an applicant score based on the criteria mentioned above, then rank students by score. Below we present more details on the scoring function for medical school applicants to Odense (see Footnote 7).

Deferred Acceptance Algorithm: Finally, the pooled rank-order lists and the program rankings (by quota) are used as inputs to a program-proposing deferred acceptance algorithm that matches applicants to programs. Each student receives at most one admission offer.

An implication of the extended rank-order-list construction is that students are considered first for quota 1 seats. A student may receive a quota 2 offer from a program only if he did not qualify for quota 1 admission.

A student who receives an admission offer can decide to accept (enroll) or reject the

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). Some medicine programs also maintain a quota 2 standby list.

offer, maintaining the option to enroll in programs with open enrollment only (without a binding GPA threshold) or re-apply to programs through the centralized application system in the future.

2.3 Dropout Rates in Medical School Programs

We focus our analysis on medical school programs in Denmark. During most of our sample period, there are three medical programs: Copenhagen, Odense and Aarhus. 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. In fact, the dropout rate at Danish medical schools is among the highest reported internationally. Mørcke et al. (2012) report a dropout rate of 20 percent at Aarhus University, which is concentrated in the first years of study. Among dropouts at Aarhus medical school, 63 percent leave in the first year 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) to 12-20 percent in Australia and the Netherlands (Ward et al., 2004; Urlings-Strop et al., 2009).[3]

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 (O'Neill et al., 2011b; Mørcke et al., 2012). Consistent with this, a sizeable fraction of dropouts struggle academically as indicated by failed exams in the early study years (Hojat et al., 1996; Yates, 2012; Maher et al., 2013).[4] In Denmark, the course curriculum is broadly standardized across medical school programs through a national accreditation agency ensuring that the content of program courses and the 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 that a student's academic fit and preparedness, which could potentially be elicited prior to admissions, is an important predictor of program completion.

[3]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 education and generous unemployment benefits contribute to high dropout rates overall.

[4]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 none of the 80 dropouts left in 'good academic standing'.

Dropouts from medical school are generally 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 students and ultimately fewer medical doctors than were planned for and needed. Universities in Denmark are publicly funded, and 80% of total funding comes from a 'taximeter scheme' that depends on students' success in the program. Specifically, a measure of "total study time" is calculated based on the number of passed exams, each of which is associated with a pre-assigned required study time. This total study time is then multiplied by a taximeter rate to determine public funding.[5] Consistent with this, we present direct evidence in Section 4 that programs consider the risk of dropout in their admission decisions. We therefore 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 its admission process in 2002. The main goal of the reform was to identify students who were 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 decrease their quota 2 share to 25 percent. This exemption allowed Odense to increase their quota 2 share to 50 percent in 2002. The quota 2 exemption from the Higher Education Act was briefly discontinued in 2008 but put in place again from 2009 onward.

Second, Odense increased their screening efforts for quota 2 candidates (see O'Neill et al. (2011a) for details). Odense introduced a required written motivational essay to assess the applicant's written communication skills, knowledge of the chosen program and profession, reflections on past experiences, on their choice of studies, and future employment plans. In addition, applicants were required to answer a questionnaire evaluating the relevance and quantity of previous work experience, educational qualifications, foreign exchange experiences, and organizational or voluntary work.[6] Students who scored well on these assignments were invited to a general knowledge test and an interview. The quota 2 score was constructed as a weighted composite of scores for qualifications, general knowledge and the admission interview.[7]

[5] See shorturl.at/uMSZ6 for more details.

[6] The questionnaire is based on a standard national application form, containing questions developed according to the national coordinated application system.

[7] The essay and the questionnaire were each scored by a single staff member on a scale from 0 to 100. The

3 Data

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

3.1 Sample Construction

Our primary data source is college application data from the Danish Central Admissions Secretariat (CAS), which provides us with information on submitted preference rankings and admission decisions for application cohorts 1994-2013. We focus on applicants who indicate either at least one medical school program or at least one program considered a close substitute to the medical programs in their submitted preference ranking. We define close substitute programs as the three most frequently listed non-medical university-level educational fields among applicants to the medical programs in Aarhus, Odense, or Copenhagen. They comprise seven programs in dentistry, psychology, and clinical biomechanics. We further include the medical school in Aalborg here as it did not open until 2010 and with a small student uptake (see Appendix A.1 for further details).[8] Our data allow us to distinguish between quota 1 and quota 2 admissions. We focus on admissions through regular quotas 10 (a subset of quota 1) and 20 (a subset of quota 2), which comprise more than 90% of all medical school admissions (see Appendix Figures 16b - 16d). 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.

We merge the college application data with several complementary data sources. First, we merge the application data with the programs' quota 2 applicant ranking lists. Second, we merge the combined data with student enrollment data, which contain the start and end dates of higher education by field of study and institution, as well as program exit codes indicating dropouts, transfers, and completion. Finally, we add population registry data which contains applicants' high school GPA, nationality, and region of residence.[9] Together,

15-minute admission test was a general knowledge test, covering many sub-domains, such as biology, physics, arts, news, music, health, and politics, with 60 multiple-choice questions. The admission interview was a semi-structured interview designed to assess the applicant's subject interest; expectations; maturity for age; social skills; stress tolerance; empathy, and general interview behavior. The test and interview performance were again scored on a 0-100 global rating scale.

[8] 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.

[9] 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.

the combined data provides us with student demographics, applications, admissions, and outcomes.

3.2 Descriptives

Our sample consists of 87,370 unique applicants to either medical schools or close substitute programs for medical schools, of which 44,694 applicants apply to at least one medical program. Copenhagen is the most popular medical program, receiving 28,580 applications ($\approx$ 1,400 per year) followed by Aarhus and Odense (see Table 1). In total, 52,182 applicants list at least one of the eight substitute programs. For Copenhagen Medical School and substitute programs, 68% of applicants list these programs first on their rank-ordered list. For Aarhus and Odense, this share drops to 44.5% and 29.2%.

The preference ranking of the medical schools changes qualitatively when conditioning on the student's former residence. Odense and Aarhus medical programs are the most popular among applicants local to their respective regions, while Copenhagen is most popular among applicants from other parts of Denmark and other countries (see also Appendix Figure 6a). Panel B of Table 1 considers application behavior conditional on submitting a quota-1 application. For instance, the second column shows that, conditional on Aarhus receiving an application, the likelihood that Aarhus is the applicant's first choice is 74% for Aarhus locals, but only 27% for Odense locals and 32% for other Danes. Analogous patterns hold for applications to Copenhagen and to Odense. This points to an important "home bias" in students' preferences.

Most students interested in the medical programs in Aarhus or Odense apply only through quota 1. Odense has the lowest share of quota 2 applicants, and in particular high-GPA applicants—i.e. applicants with a GPA of 0.3 points or more above the program's admissions threshold in the two previous years (information that is publicly available)—refrain from applying quota 2 in Odense. Only 15.4% of quota 1 applicants and 2.5% of high-GPA applicants also apply via quota 2. These low application rates are consistent with Odense's thorough screening procedure imposing high costs on applicants.

Overall, a smaller share of students with high quota 1 admission probability (high GPA) apply through quota 2. In contrast, students with low quota 1 admission chances use quota 2 more frequently, see also Appendix Figure 6b. This suggests that applicants take into account their chances of admission through quota 1 when deciding to apply through quota 2. Nevertheless, a large share of applicants without a high GPA also rely on quota 1 applications only, consistent with applicants being unconstrained in their priority lists.

Table 1: Summary Statistics: Sample Applicants, 1994-2003

Panel A: Full sample applicants	Copenhagen	Aarhus	Odense	Substitute Program
Applicants	28,580	24,200	21,639	52,182
Share listing j as 1st Priority	0.676	0.445	0.292	0.677
Admitted	10,478	7,540	4,830	9,174
Enrolled	7,866	6,391	4,071	7,662
Panel B: Application behavior for medical schools	**Copenhagen**	**Aarhus**	**Odense**	
Share listing j as 1st Priority: AAR locals†	0.275	0.741	0.212	
Share listing j as 1st Priority: ODE locals†	0.495	0.267	0.639	
Share listing j as 1st Priority: Danish†	0.763	0.324	0.204	
Share listing j as 1st Priority: Foreigner†	0.745	0.189	0.245	
Share submitting Quota 2 Application to j	0.62	0.34	0.154	
Share submitting Quota 2 Application to j: High GPA§	0.347	0.121	0.025	
GPA Cutoff Q1	9.852	9.621	9.519	
Admitted via Q1	8,694	5,921	3,007	
Panel C: Persistence outcomes	**Copenhagen**	**Aarhus**	**Odense**	
1y Dropout Rate	0.050	0.055	0.051	
3y Dropout Rate	0.121	0.132	0.122	
1y Transfer Rate	0.003	0.004	0.006	
3y Transfer Rate	0.005	0.012	0.016	
10y Completion Rate	0.834	0.839	0.830	

Note: This table presents summary statistics for our main sample, see Appendix F.1 for further details. †Regions of residence are based on the year before application and divide applicants by whether they lived in counties close to Odense, counties close to Aarhus, in any other county in Denmark, or in a foreign country, see Appendix E.1. §High GPA covers applicants with a GPA of at least 0.3 points above the highest program-specific admission threshold in the previous two years.

About 25% of applications to any medical school program are admitted, see Table 1. The largest program is Copenhagen (≈ 520 admissions per year) followed by Aarhus (≈ 375 admissions per year) and then Odense (≈ 240 admissions per year). As we document in supplementary analysis (section F.1), the number of program admissions is quite stable over time, with a modest expansion across all existing programs in 2009. At the same time, the number of applicants per year that apply to at least one medical program in Denmark gradually increased from 1,800 in the late 1990s to 3,300 after 2010. 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 (see Supplement E.2). In contrast, Odense filed an exemption from these reforms, allowing the program to maintain a quota 1 share of about 50% since 2002, see Appendix Figure 7a.

Despite being the largest program, Copenhagen is also the most competitive program during our sample period, as evidenced by a higher GPA cutoff than Odense and Aarhus. Admission thresholds are overall increasing over the sample period, see Appendix Figure 7b. About 84% of admitted students enroll in the program.

Consistent with the literature, Panel C of Table 1 shows that a substantial fraction of admitted students drop out over the course of the program. The pattern is similar across medical programs: 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%) occur 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.

Substitution patterns We focus our main analysis on admissions to Odense, where the information experiment took place, and compare with Aarhus which is the closest substitute among the medical school programs throughout our sample period. Copenhagen's program is the country's flagship program and vertically differentiated from Odense and Aarhus as evidenced by a higher GPA cutoff and the revealed popularity in student applications. As we show in more detail in Appendix Table 10, applicants rejected by Odense more commonly apply to Aarhus than to Copenhagen in a lower priority and are much more likely to be admitted at Aarhus, creating potential for spillovers that we aim to analyze.

4 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 then document the effects of intensified screening at Odense on their own and rival program dropout rates. In addition, we analyze how programs use (factors related to) applicants' residence information as a strategic response to asymmetric information. Finally, we show that two sources of interdependent values, private information held by rival programs and by applicants, play an important role in this market.

4.1 Programs' Admission Preferences

To investigate programs' objectives behind their admission decisions, we start by comparing student characteristics between quota 1 admissions and discretionary admissions through quota 2 using a regression discontinuity design (RDD). The RDD analysis focuses on applicants available to each program j, defined as applicants who were not admitted to other programs ranked higher by the student.[10]

Recall that quota 1 admissions purely depend on GPA as confirmed by Figure 1a, which plots the fraction of admitted applicants to Odense, Aarhus, or Copenhagen by quota, as a function of the difference between the applicant's GPA and the program's quota-1 GPA cutoff. As the GPA passes the GPA threshold, the probability of being admitted via quota 1 jumps to 100 percent.[11] Below the GPA threshold, we display quota 2 admission chances conditional on submitting a quota 2 application. While the pooled Figure 1a shows evidence for an increase in quota 2 admission chances in applicants' GPA, additional analysis by program in Appendix Figure 8 reveals that this pattern is entirely driven by Aarhus. In contrast, quota 2 admission rates at Odense and Copenhagen medical schools are not increasing in GPA.

To test whether admission via 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 1b presents a sharp difference in the three-year dropout rate between quota 2 and quota 1 admits at the 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:

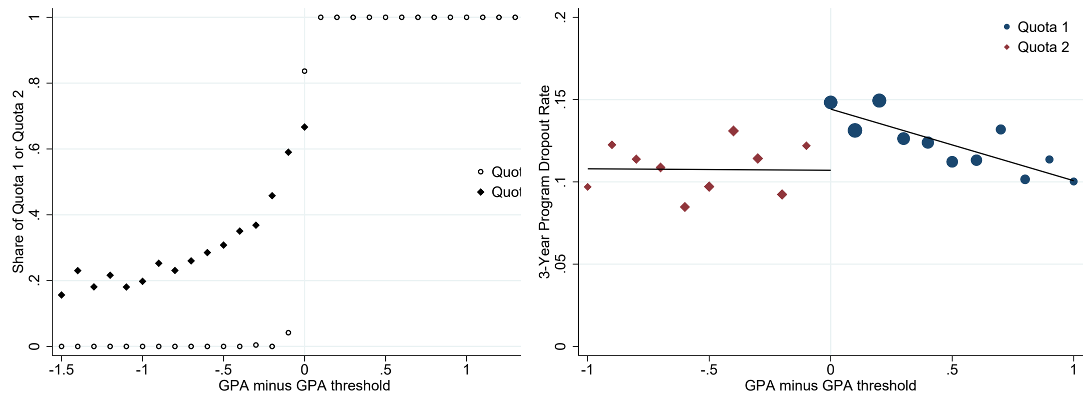
$$\begin{aligned} Y_{ijt} &= \gamma_0 + \gamma_{gpa_{q1}} \cdot gpa_{ijt} \cdot \mathbb{1}\{GPA_i \geq \text{cutoff}_{jt}\} + \gamma_{gpa_{q2}} \cdot gpa_{ijt} \cdot \mathbb{1}\{GPA_i < \text{cutoff}_{jt}\} \\ &+ \gamma_s \cdot \mathbb{1}\{GPA_i < \text{cutoff}_{jt}\} + \gamma_{jt} + \epsilon_{ijt},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

where gpa_{ijt} denotes the difference between student i's GPA and the GPA cutoff at school j, denoted as 'cutoff$_{jt}$', 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

[10] We exclude applicants admitted to a higher priority program because their admission chance at program j is zero by construction in the DA mechanism.

[11] Before 2009, older applicants were prioritized for admission at the threshold of quota 1. This practice was replaced by a lottery in 2009. Measurement error in the GPA in select sampling years explains why the quota 1 admission chance slightly exceeds 0% below the GPA cutoff.

Figure 1: Admissions and Dropouts by Quota



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

Note: Figure 1a presents admission chances for applicants to Odense, Aarhus, and Copenhagen, who are available to the respective program, as a function of the difference between student GPA and the quota-1 GPA threshold. Solid dots denote admission chances for quota 2 applicants, and hollow dots denote admission chances for quota 1 applicants. Figure 1b maintains the same horizontal axis but plots the average 3-year dropout rate on the vertical axis for enrolled students across all programs. This figure omits students admitted via quota 1 (quota 2) whose GPA is below (above) the GPA cutoff. Circle and diamond-shaped data points correspond to students admitted via quota 1 and quota 2, respectively. The lines show the best linear fit of dropouts on GPA among quota 1 and quota 2 enrollees, weighted by the number of observations in each bin.

estimate for different dropout outcome measures in the first row. We find that at the GPA cutoff margin, students admitted via quota 2 have a statistically significant 5.2 p.p. lower three-year dropout rate than students admitted via quota 1, see column 1. This difference falls slightly to 4.5 p.p when excluding transfers into other medical school programs from our dropout measure, see column 2. The results are qualitatively similar when considering alternative persistence measures such as the one-year dropout rate, completion rate, or the time to completion (see Appendix Table 11).

Columns 3–5 of Table 2 show that the effect of quota 2 screening and signaling on dropout is similar between Aarhus and Odense, but smaller at Copenhagen, which could be related to its larger share of quota 2 applicants and hence weaker self-selection compared to other programs. Mirroring the regression evidence, Appendix Figure 8 shows these patterns and the discrete difference in dropout rates at the GPA threshold for each program separately.

Evidence from Program Rankings One potential contributor to the difference in dropout rates between quota 1 and quota 2 admissions is the student selection into applying to quota 2 that cannot be accounted for by GPA. To isolate the effect of program screening efforts on outcomes, we next explore the correlation between students' quota 2 ranking at each program and dropout.[12] To this end, we conduct an RDD analysis analogous to equation (1),

[12] Alternatively, one can also revisit regression model (1) after excluding students that applied via quota 1 but not quota 2. We then find qualitatively similar effects that are about 50% smaller in magnitude but remain

Table 2: Programs' Information Quality and Student Dropout Rates

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

*Note: This table presents estimates from regression model in equation (1). Column 1 considers the three-year dropout rate at any enrolled program among admitted students to Aarhus, Odense, or Copenhagen. Column 2 excludes transfers into other medical programs in the dropout measure. All other columns include transfers. Columns 1 and 2 pool students enrolled in all three institutions, whereas Columns 3-5 analyze students enrolled in either Aarhus, Odense, or Copenhagen, respectively. All regressions include program-by-year fixed effects. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

but using the percentile rank of students admitted via quota 1 and quota 2 in each cohort, respectively, as the running variable. Specifically, in Figure 2a we rank students admitted through quota 2 from -1 for the highest-ranked student to 0 for the lowest-ranked. Quota 1 admissions are ranked from 0 for the student with the lowest GPA to 1 for the one with the highest. Note that the order is from best to worst among quota 2 students, but from worst to best among quota 1 students, such that the marginal students from each quota are comparable at 0.

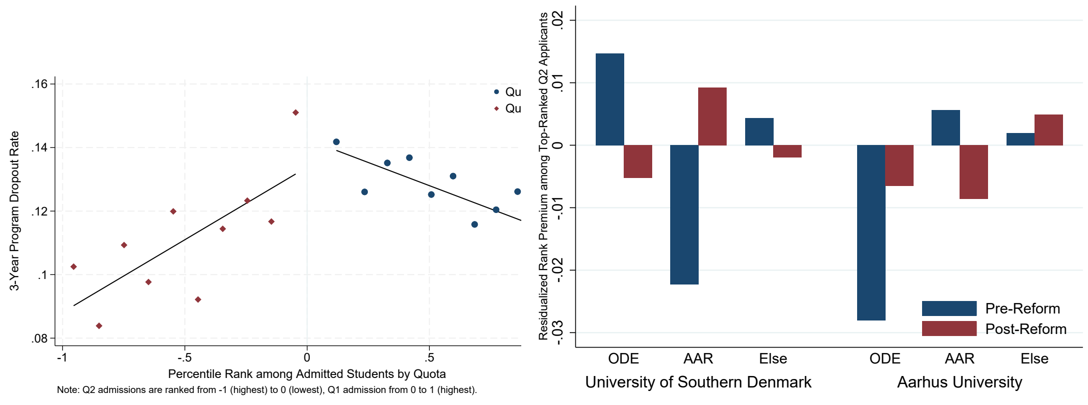
Analyzing dropout rates for the pooled sample of students at Copenhagen, Aarhus, and Odense, Figure 2a shows that the highest-ranked students admitted through quota 2 have substantially lower average dropout rates than the students with highest GPA admitted through quota 1. The clear positive slope among quota 2 students suggests that programs extract dropout-relevant information during the screening process and use this information in forming their rankings. However, analyzing outcomes separately by program in Appendix Figure 9 reveals substantial differences: While Copenhagen and Odense extract and act on dropout-relevant information in their quota 2 rankings, the ranking at Aarhus is not predictive of dropouts among quota 2 students.[13]

Finally, we investigate the correlation between a program's quota 2 percentile ranking

statistically significant, see Appendix Table 11 for details.

[13] In addition, Figure 2a suggests that the marginal admissions through quota 1 and quota 2 (around the 0 threshold in the graph) have similar dropout rates, consistent with an efficient allocation of seats across the two quotas. Results by program reveal heterogeneity and suggest that increasing the share of quota 2 seats at Odense could improve average student outcomes there, see Appendix Table 12.

Figure 2: Applicant Characteristics, Program Rankings, and Dropouts



(a) Dropouts by Rank within Quota (b) Quota 2 Rank by Applicant Residence

Note: Figure 2a plots the average 3-year dropout rate for enrolled students across all programs as a function of their percentile rank in their admission quota. Quota 2 admissions are ranked from -1 for the highest-ranked student to 0 for the lowest-ranked, while quota 1 admissions are ranked from 0 for the student with the lowest GPA admitted through quota 1 to 1 for the one with the highest. We split students into 10 equally sized bins (deciles) within each quota and lines show the best linear fit. Figure 2b presents the average rank of quota 2 applicants after controlling for cohort-GPA fixed effects. Here, applicants with a higher rank position are ranked higher by the program. We distinguish applicants based on their former region of residence, where ODE denotes students originally from the Odense region and AAR denotes those from the Aarhus region (see Appendix E.1). The sample includes applicants whose rank falls between 0.5 and 3 times the total number of available quota 2 seats.

of quota 2 applicants and persistence in other programs. To this end, we analyze outcomes among quota 2 applicants who enroll in the focal medical program but also among applicants who enroll in any other program. In addition to significant predictive power of quota 2 rankings by Odense and Copenhagen for students' success at their own programs, Table 3 shows strong evidence that higher ranked students by all three medical programs, Aarhus, Odense, and Copenhagen, have lower dropout rates if they end up studying at other programs. This suggests that programs in part learn about general applicant skills that predict persistence in many programs. Given that the ranking at Aarhus is not predictive of dropouts among medical students at Aarhus itself, see column 3, and that GPA is a stronger predictor of admissions at Aarhus (see Appendix Figure 8), the combined evidence suggests that Odense and Copenhagen conduct more targeted screening to identify more promising medical students than Aarhus.

Taken together, this evidence suggests that programs have at least some information about persistence, and care about it in their (discretionary) admission decisions, consistent with the incentives provided by government funding. There also seem to be clear differences in the quality of the information extracted during the screening process across programs, consistent with the information experiment that we analyze next.

Table 3: Quota 2 Ranking and Student Dropout Rates at Own and Other Programs

	(1)	(2)	(3)	(4)	(5)	(6)
	Odense Ranking		Aarhus Ranking		Copenhagen Ranking	
	Odense	Other	Aarhus	Other	Copenhagen	Other
rank percentile	-0.055**	-0.198***	-0.021	-0.165***	-0.072**	-0.062***
	(0.024)	(0.035)	(0.034)	(0.023)	(0.028)	(0.016)
Observations	1,664	1,258	1,252	4,569	1,461	10,049

Note: Table 3 presents the relationship between each program's quota 2 ranking percentile and students' dropout rates among enrolled students, controlling for year-by-school fixed effects, resident-location-by-school fixed effects, and year-by-GPA fixed effects. The ranking percentile ranges from 0 for the lowest-ranked applicant to 1 for the highest-ranked applicant. Columns 1-2 consider quota 2 applicants at Odense and report their dropout outcomes if they enroll at Odense (column 1), or enroll at any program except Odense (column 2). Mirroring this structure, columns 3-4 (5-6) consider quota 2 applicants at Aarhus (Copenhagen) and report their dropout outcomes if they enroll at Aarhus (Copenhagen) or elsewhere. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Interdependent Values and Odense's Information Experiment

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

To investigate these possibilities, 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).[14] We include Copenhagen in the analysis but focus on the effects on Odense and Aarhus as the closest substitute programs. We pool three cohorts into one observation, normalize the period 1999-2001 before the reform, and plot average dropout rates over time. While dropout rates followed similar trends at Odense and Aarhus before 2002, Figure 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.

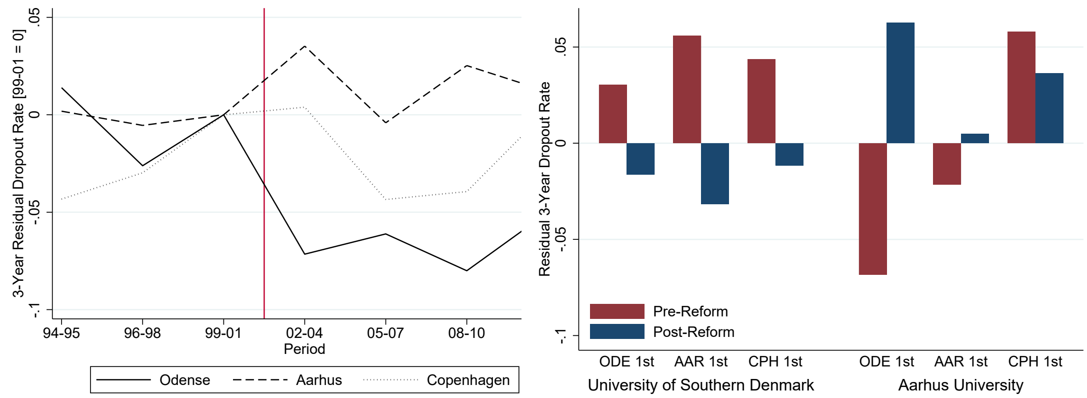
To quantify the impact of the reform on enrollment decisions and dropout outcomes more formally, we compare outcomes across medical programs before and after the reform using a difference-in-differences research design. Specifically, we estimate the regression

$$Y_{ijt} = \gamma_j + X'_{ijt}\gamma_c + \gamma_P \cdot Post_t + \gamma_{DID} \cdot Post_t \cdot Odense_{ijt} + \epsilon_{ijt}, \quad (2)$$

where $Post$ takes value 1 for the post-reform cohorts 2002-2013, and $Odense$ is an indicator for enrollment in Odense. The key parameter of interest is γ_{DID}, which captures differential

[14] We first residualize 3-year dropout rates controlling for GPA fixed effects and the share of quota 2 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 by Students' First Preference

Note: Figure 3a presents the 3-year dropout rate among enrolled students by program and student cohort (the year of program enrollment), after controlling for GPA fixed effects and the share of quota 2 admissions in each program and year. We pool 3 cohorts into one observation (2 cohorts for students enrolling in 1994 or 1995). We normalize outcomes to 1999-2001 levels by subtracting each program's mean 3-year dropout among the 1999-2001 cohorts from the other cohorts' outcomes. The vertical line indicates the timing of Odense's admission reform. Figure 3b presents the average 3-year dropout rate among enrolled students, after controlling for year and GPA fixed effects. The first three panels present dropout outcomes for students enrolled at Odense (University of Southern Denmark) by period and the student's quota 1 preference ranking. ODE 1st denotes applicants who rank Odense highest out of the three medical school programs. Likewise, AAR 1st and CPH 1st denote applicants who rank Aarhus or Copenhagen highest. The last three panels present analogous dropout outcomes for students enrolled at Aarhus.

changes in persistence among students admitted to Odense in the post-reform years. Table 4, Panel A presents this parameter estimate for different persistence measures.

First, we find that students admitted to Odense through quota 2 after the reform have a 5.1 p.p. higher probability of enrolling in the program, whereas there is no effect among quota 1 admissions. We also find that students who are admitted and enrolled at Odense after the reform have significantly lower dropout rates. The overall three-year dropout rate falls by 7.1 p.p. and this reduction remains at 4.5 p.p. when program transfers are excluded. We see qualitatively similar improvements when considering one-year dropout rates, completion rates and the time to completion, see Appendix Table 14.

Together, the evidence from Figure 3 and Table 4, Panel A, suggests that the reform helped Odense to admit 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 enrollment and dropout rates at Aarhus' medical program. Specifically, we split admitted 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.

Table 4: Student Persistence at Odense and Aarhus after the Admission Reform

	(1)	(2)	(3)	(4)
Panel A: Effects in Odense	Pr(Enroll | Q1)	Pr(Enroll | Q2)	3Y Prog Dropout Rate	3Y Med Dropout Rate
γ_{DID}	0.019	0.051**	-0.071***	-0.045***
	(0.018)	(0.023)	(0.015)	(0.014)
Constant	0.827***	0.871***	0.135***	0.121***
	(0.003)	(0.008)	(0.003)	(0.003)
Observations	17,379	5,128	18,114	18,114
R-squared	0.271	0.210	0.049	0.047

	(1)	(2)	(3)	(4)
Panel B: Effects in Aarhus	Pr(Enroll) Admitted AAR	3Y Dropout Rate Enrolled AAR	3Y Dropout Rate Ever Enrolled AAR	3Y Dropout Rate Ever Enrolled Med
Prefer Odense × Post	-0.162**	0.121*	0.159**	0.156**
	(0.059)	(0.061)	(0.062)	(0.062)
Prefer Odense	0.023	-0.029	-0.030	-0.031
	(0.059)	(0.061)	(0.062)	(0.062)
Constant	0.876***	0.129***	0.129***	0.130***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	7,036	6,251	6,674	6,732
R-squared	0.204	0.093	0.088	0.087

Note: Panel A presents estimates from equation (2). The sample includes students admitted to all three medical programs. Columns 1 and 2 report estimates for enrollment rates among quota 1 and quota 2 admissions, respectively. Columns 3 and 4 analyze program-specific dropout rates among enrolled students including and excluding transfers, respectively. All specifications control for resident-location-by-school fixed effects and year-by-GPA fixed effects. Panel B presents estimates from equation (3). Column 1 includes all students admitted to Aarhus and analyzes student dropout in the first program of enrollment. Columns 2 and 3 restrict the sample to admitted students who enroll at Aarhus in the year of their first application or ever, respectively. Column 4 extends the sample to all admitted students at Aarhus who ever enroll in a medical program. All specifications are controlled for year-by-GPA fixed effects and a home and rival student location fixed effect. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Enrollment and dropout rates among admitted students whose first choice is Aarhus are not affected by Odense's information experiment and provide a natural control group. In contrast, students who prefer Odense over Aarhus can only be admitted to Aarhus if they are rejected by Odense. Hence, these students may be adversely selected, especially after Odense's reform.

The three panels on the right of Figure 3b present the residual dropout rate, after controlling for year and GPA fixed effects, among students enrolled in Aarhus by their first preference. We focus the graphical discussion on the comparison of average pre- and post-reform dropout rates, depicted by the red and blue bars, due to a sample size limitation that makes it difficult to test for parallel trends in the pre-period. Additional evidence on the corresponding time series is provided in Appendix Figure 10. For students who prefer

Aarhus, we see stable outcomes over time. We also find steadily higher dropout rates pre- and post-reform among Aarhus students whose first preference was Copenhagen, consistent with a stable degree of adverse selection among these candidates. This stands in sharp contrast to the persistence of students at Aarhus who prefer Odense but were not admitted to Odense. Following the reform, we see a striking increase in their dropout rates, of more than 10 p.p., thus, providing evidence of an increase in adverse selection.

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

$$Y_{it} = \alpha_0 + \alpha_1 \cdot Prefer\_Odense_i + \alpha_P \cdot Post_t + \alpha_{DID} \cdot Prefer\_Odense_i \cdot Post_t + \epsilon_{it} \quad (3)$$

for student i admitted to Aarhus in year t, where $Prefer\_Odense$ is an indicator that turns on if i prefers Odense over Aarhus.

Panel B of Table 4 presents estimates of the key parameter of interest α_{DID} for admitted students to Aarhus in the first row. We find that the enrollment rate of admitted students who prefer Odense decreases by 16.2 p.p.—a substantial change in light of its average enrollment rate of 88%. We also find that the 3-year dropout rate of students who prefer Odense increases by 12.1 p.p. in the post-reform period, relative to students who prefer Aarhus (column 2). This result only considers students who enroll in the year of their first application. The point estimate increases to more than 15 p.p. for students who ever enrolled at Aarhus (column 3) or ever enrolled in a medical school program (column 4). These results suggest a substantial increase in adverse selection among admitted students to Aarhus after Odense's reform.

At the same time, the reform may have helped Odense reduce adverse selection by better identifying promising students. Indeed, Figure 3b shows that Odense faced the highest residual dropout rates in the pre-reform period among students who preferred a rival program. For these applicants, Odense achieved the largest reduction in dropout after their reform.

Discussion: The decline in dropout rates at Odense, Figure 3a, and the increase in dropout rates at Aarhus among students who prefer Odense over Aarhus, Figure 3b, is consistent with interdependent program values. After the reform, Odense may have been able to reject less talented students, which may have contributed to a winner's curse at Aarhus. We note, however, that the reform also affected the composition of quota 2 applicants, potentially affecting dropout rates. Specifically, students with moderate preferences for Odense may have refrained from applying to Odense via quota 2 if the increased screening increased their application costs. If student preferences were positively correlated with talent, this may have resulted in an advantageous student selection at Odense and an adverse student selection at Aarhus.[15] To conclude, the presented evidence suggests that Aarhus could have reduced its post-reform dropout rates if Aarhus had observed its rivals' and the students' information.

4.2.1 Program Admission Preferences and the Home Bias

Building on these insights, we next explore whether the programs' student rankings are consistent with interdependent values. While programs cannot condition on applicants' submitted preferences, they may condition on applicants' former residence, or factors correlated with it, that programs believe predict success. As discussed earlier and seen in Appendix Figure 6, applicants' former residence is a strong predictor of their preferences. We, therefore, test whether programs rank applicants differently based on their residence, conditional on GPA. Since relative rankings of inframarginal students that are far below or above the admissions cutoff may not be informative, we only include in the analysis the applicants with rank positions in the interval $[S/2,\ \ 3S]$, where S is the total number of available sets in quota 2. For this population of students, we construct a percentile ranking that ranges from 0 for the lowest-ranked to 1 for the highest-ranked applicant.

Figure 2b plots the average quota 2 rank position by applicant residency, after controlling for GPA-by-year fixed effects. Odense's ranking, depicted in the left half of the graph (blue bars), shows a clear evidence of a home bias in the pre-reform years. Students from Odense receive systematically higher rankings than expected based on their GPA. Conversely, students from Aarhus receive an implicit penalty relative to their GPA. This pattern is reversed (at smaller magnitudes) in the post-reform years; now the average ranking for applicants from Aarhus exceeds their expected outcomes based on GPA. Under interdependent values, Odense may find it useful to consider predictors of student preferences in their ranking decisions, but less so in the post-reform years as Odense collects a more informative signal of student persistence.

Turning to Aarhus, we also find evidence for a home bias in the pre-reform years as indicated by the right part of Figure 2b. Students from Aarhus receive a rank premium on

[15]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.

average, whereas applicants from Odense receive a substantial rank penalty. This home bias for Aarhus applicants is reversed in the post-reform years and the penalty for applicants from Odense decreases. Yet, Aarhus now favors students from other regions. While Aarhus does not favor local students more in response to Odense's reform, as one might intuitively expect, it could be beneficial for them to favor students from a third location instead if they are less subject to adverse selection. Alternatively, the results could suggest that Aarhus is not responding strategically to changes in Odense's signal precision and/or that Aarhus experiences concurrent changes in the composition of applicants. While applicants from Odense receive a smaller penalty, additional analysis shows that they remain at a similar disadvantage as in the pre-reform period to be ranked above the quota 2 admission bar at all, see Appendix Figure 11b. We also find that strategic considerations are less prevalent in Aarhus in the pre-reform period among the top group of applicants (Appendix Figure 11a), consistent with top credentials leaving less room for bias. Since the number of quota 2 seats decreases substantially in the post-reform period, there may be less scope for bias against applicants from Odense in later years.

4.3 Distinguishing Sources of Interdependent Values

The former discussion highlights the empirical challenges in distinguishing between two different sources of interdependent values: interdependent program values and student self-selection. Interdependent program values capture the value of rival programs' information for student outcomes at program j conditional on j's own private screening signals. In contrast, student selection captures the relationship between applicants' private information about their preferences and student outcomes at program j conditional on j's private signal. The goal of this section is to distinguish these two sources empirically.

4.3.1 Interdependent Program Values

To isolate interdependent program values, we return to programs' ranking of quota 2 applicants. We focus on Aarhus and Odense as the closest substitute programs. Specifically, we assess their relative screening precision by analyzing candidates who apply through quota 2 to both programs. To this end, we focus on a pairwise comparison of these applicants and compare the relative ranking of the two programs over the applicant pair. For any pair of applicants in a given cohort, we construct two indicators that turn on if Odense ranks student 1 above student 2 and if Aarhus ranks student 1 above student 2. This relative assessment of student quality offers two important advantages. First, it allows us to exploit the full information contained in the rankings and second, it does not require us to impose assumptions on how ranks and percentiles compare between programs in a given cohort.

The dependent variable is the relative comparison of dropout outcomes, which equals 1 if student 1 drops out and student 2 does not. The outcome equals 0 if both students or none of them drop 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, resident location, and GPA fixed effects. We account for the correlation patterns in the dyadic data by using two-way clustering at the individual level.

The results in Table 5, column 1, first show that Aarhus and Odense rarely agree on the relative ranking of a pair of candidates. The relationship is positive and statistically significant, but Odense ranking one student over the other student increases the odds that Aarhus does the same by 6.2 p.p. only. 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's ranking predicts dropouts conditional on Aarhus' signal. This is also the case when restricting attention to pairs of students that both enroll in other programs than Odense, see column 4. Finally, we split the full sample of pairs between the pre- and post-reform period, see columns 5 and 6. For Odense, the coefficient increases from 4.6 p.p. to 13.2 p.p. in the post-reform period and becomes significant at the 1% level. Yet, because of the smaller sample size in the pre-2002 period, we are slightly underpowered to reject that the two coefficients are the same. For Aarhus, we find a small improvement over time but post-reform screening remains at a small coefficient of 2.1 p.p. that is statistically insignificant.

We further analyze Odense's screening precision using analogous pairwise regressions for applicants who apply to both Copenhagen and Odense, or to Copenhagen, Odense, and Aarhus, in Appendix Table 13. While we find that Copenhagen's signal predicts student outcomes, Odense's signal remains highly informative conditional on information by one or both rivals. Results in all subsamples are consistent with an improvement in information quality at Odense after their screening reform.

Overall, our findings indicate that Odense holds private information that predicts dropout outcomes at Odense and elsewhere, even when conditioning on the information held by its rivals. Our results also suggest that Aarhus, as the closest substitute program, could reduce

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

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	AAR 1>2	Difference in 3Y Dropout for Student 1 versus Student 2				
Sample	All	All	Both ODE	None ODE	Pre-2002	Post-2002
	Both ranked	Both enrolled	Both Enrolled	Both enrolled	Both enrolled	Both enrolled
ODE Ranks 1>2	0.062***	-0.126***	-0.029*	-0.061**	-0.046	-0.132***
	(0.017)	(0.018)	(0.017)	(0.028)	(0.034)	(0.019)
AAR Ranks 1>2		-0.018	-0.020	-0.031	-0.005	-0.021
		(0.016)	(0.016)	(0.028)	(0.034)	(0.017)
Observations	67,977	62,979	21,731	12,661	6,286	56,693
R-squared	0.036	0.075	0.101	0.101	0.103	0.086

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

their dropout rates if it knew and acted on the information on completion rates possessed by Odense. Finally, our findings suggest that Odense's informational advantage increases significantly in the post-reform period.

4.3.2 Student Self-Selection

To isolate the effects of student self-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 outcomes including enrollment and program dropout. Table 6 presents the results from linear regressions of persistence outcomes on an indicator of a quota 2 application. Column 1 shows that students who applied via quota 2 have a 1.7 p.p. higher enrollment rate conditional on admission.[16] Column 2 shows that quota 2 applicants who enroll in the program have 2.7 p.p. lower 3-year dropout rates. This relationship remains unchanged when excluding transfers (column 3). Completion rate effects (column 4) are slightly larger, but we find no differences in average study time until graduation (column 5).

Together, our findings suggest that student preferences and the decision to apply via quota 2 predict enrollment and dropout outcomes, and provide strong evidence for student self-selection as a source of interdependent values.

[16]These regressions control for GPA fixed effects given the strategic quota 2 application behavior depending on GPA documented in Appendix Figure 6b. We also include program-by-year and program-by-location fixed effects to reflect changes in capacities and geographic preferences of applicants.

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

	(1) Enrollment	(2) 3Y Prog Dropout	(3) 3Y Med Dropout	(4) Completion	(5) Study Time
Applied Quota 2	0.017*	-0.027***	-0.025**	0.035**	-24.548
	(0.009)	(0.010)	(0.010)	(0.015)	(16.758)
Constant	0.827***	0.130***	0.120***	0.835***	2,596.7***
	(0.003)	(0.003)	(0.003)	(0.004)	(4.7)
Observations	7,652	6,605	6,605	4,693	3,915
R-squared	0.174	0.026	0.022	0.025	0.095

*Note: This table presents the effects of applying via quota 2 on outcomes among students admitted via quota 1. The sample includes students enrolled in either Aarhus, Odense, or Copenhagen medical school through quota 1 admission. All regressions include program-year fixed effects, program-location-of-residence fixed effects, and GPA fixed effects. Column 1 reports enrollment rates. Column 2–3 report results for the 3-year dropout rates, with column 2 analyzing program-specific dropout and column 3 excluding transfers. Column 4 reports completion rates for cohorts starting in 1994-2009. Column 5 reports study time to completion for graduates from cohorts 1994-2009. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

5 Model

We now specify a structural model, motivated by this empirical evidence, that allows us to quantify the impacts of interdependent values and student self-selection on patterns of enrollment and persistence.

Markets and Programs: Let $t \in \{1994, 1995, \dots, 2013\}$ denote a market (an entering cohort). In market t, each program $j > 0$ has $m_{jkt} \in \mathbb{R}_+$ quota k seats, for $k \in \{1, 2\}$.

We focus on the medical programs at Odense, Aarhus, and Copenhagen, which we denote $j = 1, 2, 3$, respectively. We model applicants' choice of quota 1 and quota 2 applications to these programs, the programs' choice of quota 2 admissions rankings, and persistence/dropout rates for students matched to them. In addition to these options, we include in students' quota 1 choice sets an "on-platform" outside option, $j = 4$, representing non-medical university programs in Denmark, as well as an "off-platform" outside option, $j = 0$.[17]

Students: There is a continuum of students $\mathcal{I}_t$, of mass μ_t, who participate in market t and may submit applications to programs $j \in \{1, 2, 3, 4\}$. Each student i is characterized by a type vector

$$(x, u, \omega, s, c)_i \sim F_t(u, \omega, s, c|x)Q_t(x),$$

[17] While we focus on medical programs, all university programs in Denmark participate in the centralized match. An "on-platform" outside option is needed to fit the data, and to rationalize medical applicants' qualifying for admission to some medical program but placing elsewhere. In the data, $j = 4$ consists of the union of a set of programs that are close substitutes to medicine. We provide details in Appendix A.1.

where:

- x_i is a vector of applicant characteristics, with measure $Q_t(\cdot)$ over a finite set X. In our empirical model, it consists of a constant, GPA, and indicators for Odense locals, Aarhus locals, and foreign (non-Danish) applicants. It is commonly observed by all market participants. In estimation, we will observe it as well.

- $u_i \in \mathbb{R}^4$ is a vector of utilities, privately known by the student. In the event the student is matched to program $j > 0$, he receives a payoff $u_{ij} \in \mathbb{R}$. We normalize the outside option $u_{i0} = 0$ for all i.

- $\omega = (\omega_{i1}, \omega_{i2}, \omega_{i3}) \in \mathbb{R}^3$ is the student's "talent" for studying medicine. The term $\omega_{ij} \in \mathbb{R}$ enters program j's payoff in the event that student i is matched to j. It is not observed by any agent.

- $s_i = (s_{i1}, s_{i2}, s_{i3}) \in \mathbb{R}^3$ is a vector of signals of student ability and motivation. The signal $s_{ij} \in \mathbb{R}$ is privately observed by program j in the event student i submits a quota 2 application to j. Otherwise, it is not observed.

- $c_i \in \mathbb{R}^3$ are quota 2 application costs. To submit a quota 2 application to program j, a student pays a cost c_{ij}. These costs are privately observed by the student.

The conditional distribution $F_t(u, \omega, s, c|x)$ has a continuous positive density, $f_t(u, \omega, s, c|x)$ for all x.

Timing: First, each student $i \in \mathcal{I}$ simultaneously observes her own $(X_i, u_i, c_{i\cdot})$ and chooses an application. In particular, she chooses a rank-order list (ROL) ℓ_i^1, consisting of any subset of $\{1, 2, 3, 4\}$ in any order, which determines her quota 1 applications, and chooses whether to submit a quota 2 application, $A_{ij} \in \{0, 1\}$, to each school listed in ℓ_i^1. As in the data, student i is required to submit a quota 1 application in order to apply via quota 2. While it is free to submit a quota 1 application, submitting a quota 2 application to program j requires incurring a cost c_{ij}, representing the time required to sit for exams, write a statement of purpose, and/or fulfill other program-specific requirements.

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*

$$r_{j2} : X \times \mathbb{R} \to [0, 1] \cup \{\emptyset\},$$

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 $r_{j2}(X_i, s_{ij})$ 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_{j1t} and $j^{(2)}$ with capacity m_{j2t}.

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_{j2}. Students for whom $r_{j2} = \emptyset$ are omitted (declared unacceptable).

4. Students' rank-order lists 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 program-proposing DA algorithm produces a matching. In iteration $t \geq 1$, each pseudoprogam $j^{(k)}$ points to a measure m_{jkt} of its most-preferred students that have not yet rejected it; students reject unacceptable programs and keep their most preferred acceptable program. This step is repeated until convergence.

Once the procedure terminates, students learn their placements. In our setting this algorithm clears the market and yields the unique matching that is stable with respect to the submitted ordinal preferences. This matching can be represented by cutoffs, i.e. a GPA cutoff for each quota 1 pseudoprogram and a cutoff value for each quota 2 pseudoprogram (Azevedo and Leshno, 2016, Theorem 1), as we discuss below.

Allocations and Payoffs: Student i receives

$$u_{ij} - \sum_j A_{ij} c_{ij}$$

if she submits quota 2 applications A_i and matches to program $j \geq 0$. 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. Let $\ell(u, c, x) = (\ell^1(u, c, x), A(u, c, x))$ denote a student strategy profile—a mapping from students' information to quota 1 rank-order lists and quota 2 applications—which we assume is pure almost everywhere. Let $r(\cdot)$ be a profile of the ranking functions of each program and quota. For quota 2 admissions, this function is chosen by the program as described above. For quota 1 admissions, $r_{j1}(s_j, x)$ exogenously ranks applicants in order of their GPA, which is an element of x. Let the vector $\underline{r}^{(t)} = \{\underline{r}_{jk}^{(t)}\}_{j\in\{1,2,3\},k\in\{1,2\}} \in [0,1]^6$ denote the minimum score among students provisionally held by each pseudoprogram in iteration t, and let[18] $\underline{r} = \lim_{t\to\infty} \underline{r}^{(t)}$ denote the minimum score among students matched to each pseudoprogram (equivalently: the "cutoff" percentile rank at each pseudoprogram) in the final allocation.

Let $D_{jk}(x, \underline{r}; \ell, r) \subset \{i \in \mathcal{I}_t : x_i = x\}$ be the set of students with observables equal to x who are available to program j via quota k given cutoff vector $\underline{r}$. In the case $k = 1$ this set consists of all quota 1 applicants to j who have not ranked any program and quota above j to which they will be admitted. For the case $k = 2$, the set $D_{jk}(x, \underline{r}; \ell, r)$ consists of students who have submitted a quota 2 application to j, and have not ranked any program and quota above j to which they will be admitted.

Pseudoprogram (j, k) receives ω_j from each student it is matched to. A student i of type x is matched to pseudoprogram (j, k) if $i \in D_{jk}(x)$ and $r_{jk}(s_{ij}, x) > \underline{r}_{jk}$. Hence, the pseudoprogram's payoff is

$$\Pi_{(jk)}(r, \ell) = \int_X \int_{D_{jk}(x,\underline{r};r,\ell)\cap\{r_{jk}(s_j,x)\geq\underline{r}_{jk}\}} \omega_j \, dF(u, \omega, s, c|x) dQ(x).$$

Analysis: The outcome of the algorithm coincides with student-proposing DA in a large market (Azevedo and Leshno, 2016). Therefore, since quota 1 applications are free, 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^1 truthfully. We assume that students do so, applying to all programs j such that $u_{ij} > 0$, in descending order.

The optimal quota 2 decision depends on programs' strategies, and on students' beliefs about admissions chances. We provide a worked example of the quota 2 application decision in Appendix G.1. We make the following behavioral assumption on programs' strategies.

Assumption 1 (Truthful Ranking) *Let students' strategies be given by $\ell^* = (\ell^1, a^*)$. Each program j ranks quota 2 applicants according to their expected payoff conditional on*

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

matching to j, that is, $r_{j2}(s_{ij}, x) > r_{j2}(s'_{ij}, x')$ if and only if

$$E(\omega_{ij}|s_{ij}, i \in D_{j2}(x, \underline{r}; \ell^*, r), x) > E(\omega_{ij}|s'_{ij}, i \in D_{j2}(x', \underline{r}; \ell^*, r), x').$$

This assumption says that programs are sophisticated about interdependent values, and about 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.[19]

Students form rational expectations about quota 1 and quota 2 admissions chances in equilibrium, given knowledge of their GPA, location, and utilities. We assume that students correctly anticipate the relevant quota 2 admissions cutoffs, $\underline{r}_{\cdot 2}(x)$, as well as the GPA cutoffs for quota 1 admission in their market. Students face admissions uncertainty because they do not observe their signal realization s_i, only its conditional distribution given their utility vector u_i.

In estimation, we restrict attention to ranking functions that prefer higher signal values to lower signal values, conditional on x. We define an equilibrium (r^*, ℓ^*) as a profile of program rankings and student application such that students choose their application portfolio optimally, given the programs' strategies, and given the students' portfolios programs' strategies satisfy Assumption 1.

Assumption 2 (Increasing Ranking) *In the equilibrium (r^*, ℓ^*) that is played, each program program j's quota 2 best-response ranking function $r^*_{j2}(s_j, x; \ell^*, r^*_{-j}(\cdot))$ is increasing in s_j for all x.*

When programs use increasing rankings, there exist program-specific cutoff functions $\underline{s}_j(x)$ such that $r_{j2}(\underline{s}_j(x), x) = \underline{r}_{j2}$. Students of type x match to pseudoprogram $(j, 2)$ if and only if they belong to $D_{j2}(x)$ and have $s_j \geq \underline{s}_j(x)$. Hence, to describe equilibrium allocations, we may restrict attention to "cutoff functions" $\underline{s}_j(x)$. These objects are simpler

[19]In general, in many-to-one stable matching mechanisms, programs may have incentives to engage in capacity reduction, or to declare some applicants unacceptable (Sönmez, 1997). In our setting, the government sets binding constraints on programs' capacities and quota 2 shares, such that programs would not wish to further reduce capacities. However, a program might wish to discriminate against students who are likely to set off "rejection chains". Intuitively, if a student, i, prefers program j but would attend program k if he is rejected by j, then if program j rejects the student, this rejection 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 F.3 suggests that the potential for successful rejection chains is very limited in our setting. Our assumption abstracts from these incentives.

than the full rankings and suffice for students' decisions. To calculate admission odds, a student need only calculate the probability $Pr(s_j > \underline{s}_j(x)|u, x)$.

Assumption 2 allows us to restrict attention to monotone strategies in our empirical analysis. However, it is an assumption on best responses, not primitives. We provide two additional results. First, we provide a sufficient condition for Assumption 2 that can be verified given parameters and cutoffs. Second, we provide primitive conditions that imply Assumption 2. We show that it holds for all parameter values under a standard MLRP assumption relating signals s_j and payoffs ω_j, and a condition requiring conditional independence of rival programs' signals s_j and s_k conditional on the vector of talents ω. In fact, this primitive condition ensures a stronger version of Assumption 2 in which the best response rankings are increasing in signals for any student application strategy profile ℓ. An implication is that all equilibria are in cutoffs. We state the conditions formally and prove our results in Appendix B.

While conditional independence of signals is a common assumption in empirical auctions, in our context this latter assumption rules out variation in common "interview skill" conditional on students' propensities to graduate. We do not impose it in estimation.

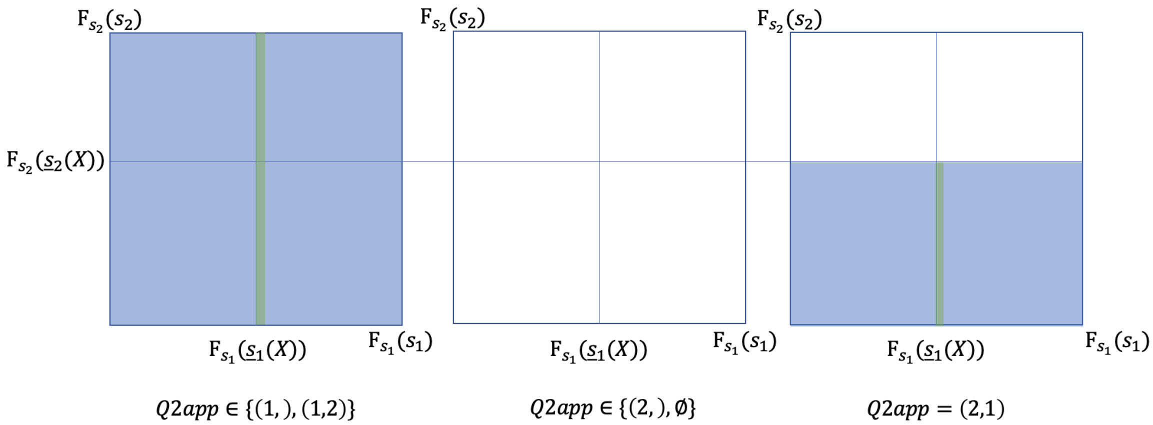
Equilibrium Cutoffs: Figure 4 illustrates programs' strategies and students' assignments. Fix a set of cutoffs for quota 1 and quota 2 admission. For simplicity, we restrict attention to two programs, denoted 1 and 2, and consider a value of x at which students do not qualify for quota 1 admission. Each cell plots quantiles of program 1's signal, s_1, on the x-axis, against quantiles of program 2's signal s_2 on the y-axis. We shade the region $D_{12}(x)$, the set of students available to program 1. These students either prefer program 1 (top-left panel), or prefer program 2 to 1 but have a sufficiently low signal s_2 that program 2 will reject them (top-right panel). Students belonging to $D_{12}(x)$ with signals $s_1 \geq$ the cutoff value $\underline{s}_1(x)$ are matched to program 1. We highlight students at the margin: those belonging to $D_{12}(x) \cup \{s_1 = \underline{s}_1(x)\}$.

An implication of Assumption 1 is that the expected value of the marginal student at program j must be equated across values of x within a market: for some $\underline{\omega}_j$, we have $E(\omega_{ij}|s_{ij} = \underline{s}_j(x), i \in D_j^2(x, \underline{r}; \ell^*, r), x) = \underline{\omega}_j \; \forall x$.

5.1 Parametric restrictions for estimation

The evidence on the winner's curse, on selection on students' application decisions, and on heterogeneity across programs motivates us to construct a tractable empirical model of a two-sided matching market with asymmetric interdependent values. Given limited data, we

Figure 4: Quota 2 Cutoffs and Available Applicants



Note: this figure illustrates cutoffs and applicants at a particular value of x. Each cell denotes a set of quota 2 applications. Left cell: applicants whose highest-ranked quota 2 application is to program 1. Middle cell: no quota 2 application to program 1. Right cell: prefer program 2 to program 1, apply quota 2 to both. Each box plots quantiles of s_1 (x-axis) against quantiles of s_2 (y-axis). Blue shaded region denotes $D_{12}(x)$, the set of applicants available to program 1 via quota 2. Students in $D_{12}(x)$ with signals $s_1 \geq \underline{s}_1(X)$ are matched to program 1. Green region denotes students "at the margin," i.e. with signal values equal to the cutoff who are matched to program 1.

impose parametric assumptions for estimation.

We assume $x \sim Q_t(x)$, allowing the distribution of "observables" to differ arbitrarily across cohorts. We take this distribution from the data. We allow primitive parameters to change at the time of Odense's reform but hold them fixed within the pre-reform and post-reform periods. Let $\tau(t) = 1(t \geq 2002)$ be an indicator for the post-reform period. Cutoffs will vary by year to match supply to demand.

Utilities and signals: Utilities and signals are jointly normally distributed, with parameters that may change post-reform. We assume,

$$u_{ijt} = x_i'\gamma_{j\tau(t)} + \varepsilon_{ijt},\ j \in \{1,2,3,4\},$$

and place a factor structure on the covariance of utility shocks and signals as follows:

$$\varepsilon_{ijt} = \rho^0_{\varepsilon_{j\tau(t)}}\tilde{\varepsilon}_{i0t} + \tilde{\varepsilon}_{ijt},\ j \in \{1,2,3,4\} \tag{4}$$

$$s_{ijt} = \rho^{\varepsilon 0}_{s_{j\tau(t)}}\tilde{\varepsilon}_{i0t} + \rho^{\varepsilon ijt}_{s_{j\tau(t)}}\tilde{\varepsilon}_{ijt} + \rho^{\varepsilon i4t}_{s_{j\tau(t)}}\tilde{\varepsilon}_{i4t} + \rho^{s0}_{s_{j\tau(t)}}\tilde{s}_{i0t} + \rho^{j}_{s_{j\tau(t)}}\tilde{s}_{ijt},\ j \in \{1,2,3\} \tag{5}$$

$$\tilde{\varepsilon}_{i0t}, \tilde{\varepsilon}_{i1t}, \tilde{\varepsilon}_{i2t}, \tilde{\varepsilon}_{i3t}, \tilde{\varepsilon}_{i4t}, \tilde{s}_{i0t}, \tilde{s}_{i1t}, \tilde{s}_{i2t}, \tilde{s}_{i3t} \sim N(0,1)\ i.i.d. \tag{6}$$

That is, an agent's payoffs depend on preference shocks $\tilde{\varepsilon}_{i0t}$ common to the inside options, and on idiosyncratic shocks $\tilde{\varepsilon}_{ijt}$. Signals depend on these shocks, on preference shocks for the non-medical program $\tilde{\varepsilon}_{i4t}$, on idiosyncratic shocks $\tilde{s}_{ijt}$, and on a common "interview skill" shock $\tilde{s}_{0it}$. As a scale normalization, we choose parameters ρ such that the variance of s_j is equal to 1, for $j = 1, 2, 3$. The value s_j may be interpreted as the z-score of the signal conditional on the candidate's observables x.

Persistence and Program payoffs: Programs prefer students who are more likely to persist. In addition, programs may have "non-graduation" preferences over the characteristics x of students. For example, a program may exogenously prefer locals, or high-GPA applicants, for quota 2 slots to a greater extent than would be justified by picking the academically strongest class, because it believes that these students "deserve" those slots.

We say that a student who is matched to a program *persists* if he/she remains enrolled in the same program three years later. A student i who is matched to program j persists in the event that the latent variable $\omega^*_{ijt} = x_i\alpha_j + \tilde{\omega}_{ijt}$ is greater than zero. We write the value of year t applicant i to school j as

$$\omega_{ijt} = Pr(x_i\alpha_j + \tilde{\omega}_{ijt} > 0) + \pi_j(x_i),$$

where $\pi_j(x_i)$ represents non-graduation preference weights. We hold the weights α_j on GPA and location fixed over time within programs. That is, while the informational environment may change with Odense's reform, we are assuming that the persistence-production technology is stable, consistent with the lack of other changes in medical programs' curricula or standards.

One may interpret ω^*_j as a potential outcome. In the event that the student matches to j, we observe its realization. Because a student matches to at most one program in a given cycle, it is not possible to observe both $1(x\alpha_j + \tilde{\omega}_j > 0)$ and $1(x\alpha_{j'} + \tilde{\omega}_{j'} > 0)$ for $j' \neq j$. For this reason, we specify the marginal distribution of ω^*_j conditional on the vector of signals and utilities. We assume that $\tilde{\omega}_j|u, s$ is conditionally normally distributed. In particular, let $\overline{\omega}_{it} \equiv \overline{\rho}_1 s_{i1t} + \overline{\rho}_2 s_{i2t} + \overline{\rho}_3 s_{i3t} + \overline{\rho}_4 \varepsilon_{i4t} + \overline{\rho}_0 \varepsilon_{i0t}$. We assume

$$\tilde{\omega}_{ijt} = w_{j1}\overline{\omega}_{it} + w_{j2}\varepsilon_{ijt} + w_{j3}s_{ijt} + w_{j4}\tilde{\tilde{\omega}}_{ijt}, \tag{7}$$

where $\tilde{\tilde{\omega}}_{ijt} \sim N(0, 1)$, independently of (ε, s). That is, $\tilde{\omega}_j$ may depend on the vector of signals and utility shocks in a common way across programs, but the own-program preference and signal, ε_j and s_j respectively, may have additional weight. As a scale normalization, we assume the weights are such that the (unconditional) variance of $\tilde{\omega}_j$ is equal to 1. In addition, because one may freely multiply the $\overline{\rho}$ by a constant and divide w_{j1} by this constant, we fix the weight on this common index to 1 for an arbitrary program.

We do not take a stand on the joint distribution of $\tilde{\omega}$. Our functional forms are consistent with the vector $(\varepsilon, s, \tilde{\omega})$ being jointly normally distributed. However, we do not specify $cov(\tilde{\omega}_j, \tilde{\omega}_{j'})$, nor does this object enter the likelihood.

Program cutoffs: In estimating the model, we place a parametric assumption directly on the cutoff signal values $\underline{s}_{jt}(x)$:

$$\underline{s}_{jt}(x_i) = x_i\beta_{j\tau(t)} + \beta_{0jt}. \tag{8}$$

That is, program j's cutoff is a linear function of x, plus a year-specific intercept reflecting current market conditions. For example, if a year has an unusually large number of applicants, the cutoff may be higher. Parameters $\beta_{j\tau(t)}$ vary by program and period in estimation. Weights $\beta_{j\tau(t)}$ and β_{0jt} are equilibrium-specific, and will vary under counterfactuals.

Linearity in x is not essential. In principle, one could allow the cutoff to vary with a rich set of transformations of the observables. In the extreme, one could include indicators for each value in x's support, allowing a fully flexible cutoff function. Given the relatively small sample sizes within each cell in our data, however, attempts to recover this cutoff function from the data would be noisy. Our specification allows us to interpret elements of β as equilibrium bonuses or penalties for location and GPA in programs' admissions decisions.

Admissions chances: Applicant i correctly anticipates the equilibrium cutoffs $\underline{s}_{jt(i)}$ in his market, where $t(i)$ denotes i's cohort. Applicants form posterior beliefs over their vector of signals, and hence their admission chances, given knowledge of their observables x_i and utility shocks $(\varepsilon_{i1}, \ldots, \varepsilon_{i4})$.

Forming an optimal portfolio requires beliefs about quota 1 admissions chances as well. We model these, allowing for uncertainty about quota 1 cutoffs as follows. The data are divided into small cells based on GPA, location, and year. Within a cell, applicants' admissions chances are drawn by sampling GPA uniformly and then comparing it to the observed GPA cutoff. For instance, if the observed cutoff at Odense is 9.6, and the cell's GPA range is from 9.5 to 9.7, then the applicant has a 50% chance of admission via a quota 1 application.

Application costs: Quota 1 applications are free. To submit a quota 2 application to a set $K \subseteq \{1,2,3\}$, a candidate pays $\sum_{j \in K} c_{ij}$ with $c_{ij} \sim N(\delta_{j\tau(i)}, \sigma_j^2)$, where $\tau(i)$ indicates whether i's cohort, $t(i)$, is a post-reform cohort. That is, mean costs may differ with Odense's reform, but for interpretability, we hold the variance of costs fixed. Costs are independent across programs.

Outside options: We do not model the decision to submit a quota 2 application to the outside option $j = 4$. Instead, we allow only quota 1 applications to this program, but model admissions chances as a function of x: $pr(admit_4) = \Phi(x\beta_\tau^{oo})$, where $admit_4$ is an indicator for admission to the outside option. This flexibility captures the fact that option $j = 4$ in fact consists of heterogeneous programs. We hold these chances fixed under counterfactuals.

6 Estimation

6.1 Estimation Procedure

Estimation proceeds in two steps. First, we jointly estimate programs' quota 2 admission cutoffs and all parameters except the "non-graduation preferences" $\pi(\cdot)$ via GMM. In the second step, we impose the optimality of programs' quota 2 rankings to recover non-graduation preferences $\pi(\cdot)$. Estimation does not involve solving the equilibrium model, nor do we assume optimality of programs' decisions in the first step.

Our approach to step 1 combines ideas from the differentiated-products demand-estimation literature (Berry et al., 1995, Berry et al., 2004) with "indirect inference" moments (Gourieroux et al., 1993). In two-sided matching markets, programs' cutoffs equate demand with the supply of seats, analogously to prices in standard settings (Azevedo and Leshno, 2016). As in demand estimation, we condition on the cutoffs that are in the data, and assume agents take them as given. We observe the realized GPA cutoffs for quota 1 admission in each year. While quota 2 cutoff signal values are not directly observed, they can be recovered from the data. At a given vector of observables x, programs' cutoffs $\{\underline{s}_{1t}(x), \underline{s}_{2t}(x), \underline{s}_{3t}(x)\}$ are such that the model-predicted measure of applicants matched to each program with observables x is equal to the share in the data in year t.

As in "indirect inference," we minimize the distance between the coefficients of a set of auxiliary models, estimated on the data, and and the corresponding coefficients' values as implied by the model. We consider the following endogenous outcomes: quota 1 and quota 2 applications, quota 2 admissions, being ranked highly in a program's quota 2 list, placement in a program and quota, and three-year persistence. The auxiliary specifications regress indicators for these outcomes on exogenous characteristics of students and indicators for prior endogenous outcomes.

The second step exploits an implication of optimality. If a program were to maximize persistence, then the persistence rates of the marginal matched student at each value of x in a given year should be equated, up to non-graduation preferences. If $\pi(x) = 0$ for all x, marginal students at program j at each value of x should have equal graduation rates. To the extent that local students (or foreigners, rival-local students, or students with high GPAs...) matched to program j with signals just above j's cutoff perform worse (or better) than marginal nonlocals, non-graduation preferences must rationalize the difference.

We formally define the estimator in Appendix C.1. We describe the moments in Appendix C.1.1, give computational details in Appendix H.1, and provide the full list of moments in Supplementary Appendix H.3.

6.2 Design

Identification of preferences is standard. Because quota 1 applications are truthful, and we observe application portfolios, we can recover the joint distribution of ordinal preferences for those options conditional on x. This distribution is then held fixed in counterfactuals.

By matching LPM moments, we force the model to fit impacts of policy changes, and of quota 2 applications and admissions, discussed in previous sections. Our procedure exploits differences between the persistence rates of quota 1 and quota 2 admits, and statistical relationships between persistence and applicants' preferences and quota 2 decisions.

Moreover, our procedure implicitly uses policy variation to pin down persistence parameters. We assume that the parameters α that govern persistence are invariant to Odense's reform, while other parameters may change. As selection into programs and quotas varies with the policy reform, and hence the unobserved preference shocks and signals of matched students differ with the reform, we can recover the relationship between those unobservables and persistence. In the absence of policy variation, an alternative would be to exclude location (or some other observable that shifts the probability of matching to j) from persistence equations. We do not exclude location, but hold its effect fixed.

7 Results

In this section, we present a summary of the model fit and provide an interpretation of the key parameter estimates. Full details on parameter estimates are in Appendix Section C.2.

In addition to our main specification, to investigate the importance of interdependent values we estimate an alternative model with private values. This model is identical to our main specification except that the parameters w_{j1} and w_{j2} in equation (7), which capture the effects of students' preferences and rival programs' signals on outcomes, are constrained equal to zero for all programs.

7.1 Model Fit: Targeted Moments

Table 7 summarizes the model fit of application behavior, admissions, and outcomes by program and period. The first four panels summarize aggregate application and admission outcomes across programs and quotas in the pre- and post-period. We target these outcomes directly in the estimation, and the model matches the data patterns closely. For example, the model closely replicates that Copenhagen is the most popular program, receiving the largest number of quota 1 applications and the highest share of applications that are accompanied by a quota 2 application. Across all programs, we match the share of quota 1 seats in the pre-period. The model captures that Odense then expanded their share of quota 2 seats (and matches) in the post-period as discussed in Section 2, whereas Aarhus and Copenhagen allocate a larger fraction of their overall seats via quota 1 in the post-period.

The last panel displays the share of students that persist for at least three years (enroll and do not drop out) among matched students. The model closely matches the persistence rates before and after the reform across programs and predicts (consistent with the data) an increase in persistence at Odense and a decrease at Aarhus after the reform.

Consistent with the data, our model estimates also show that applicants prefer and are more likely to persist in local programs (conditional on GPA), which in turn often select them preferentially. Foreign applicants on the other hand have lower persistence rates and face admissions disadvantages, see Appendix Section H.3 for details.

7.2 Model Fit: Untargeted Moments

We also revisit the model fit of several empirical results from Section 4 that we do not explicitly target in the estimation. Throughout this analysis, we compare the fit of our main model to that of our private-values specification.

We start with the regression analysis outlined in equation (2) and present the DID effect on persistence in the first row of Table 8.[20] In the data, we estimate an increase in persistence

[20]A student who is matched to a program is said to persist if they enroll and subsequently do not drop out within three years. This outcome variable combines the enrollment decision examined in columns (1) and (2) of Table 4 and (non-)dropout conditional on enrollment as examined in column (3) of Table 4.

Table 7: Model Fit: Applications, Admissions, and Outcomes by Program and Period

	Data			Model		
	Aarhus	Odense	CPH	Aarhus	Odense	CPH
Quota 1 Applicants						
Pre	6826	5765	9045	6980	4812	8990
Post	17299	15747	19514	15922	11838	20291
Share Q2 Apps						
Pre	.235	.13	.675	.235	.157	.68
Post	.382	.162	.595	.413	.214	.572
Matches/ Admissions						
Pre	2187	1482	3400	2171	1457	3427
Post	4941	3251	6245	4558	3034	5644
Share Matched via Quota 1						
Pre	.663	.752	.727	.62	.718	.72
Post	.839	.557	.866	.787	.496	.815
Share Persist						
Pre	.77	.687	.697	.764	.698	.698
Post	.756	.78	.711	.758	.772	.716

Note: This table compares model estimates of the number of applicants, matches, and outcomes by program and period to their sample counterparts. "CPH" is the abbreviation for Copenhagen, "Pre" denotes the pre-period ranging from 1994-2001 and "Post" denotes the post-period including the years 2002-2013. The first panel presents counts of the number of quota 1 applications received by the respective program in the given period. The second panel summarizes program-specific quota 2 applications as a fraction of the program-specific quota 1 applications. The third panel summarizes the number of students matched to a given program. These students must be above the bar in the focal program and below the bar for higher-ranked programs in the student's ROL. The fourth column displays the fraction of students matched via quota 1 out of all matched students to the specific program. Finally, the last panel summarizes the share of matched students that enroll and persist for at least three years in the program.

of 12.4 percentage points at Odense following the reform. In the simulated data, we find a smaller yet positive increase of 5.5 percentage points, displayed in the third column. Part of the increase can be attributed to the estimated increase in Odense's quota 2 application costs, see Appendix Table 17, which gives students an opportunity to signal their preference for Odense (Spence, 1973). The last column considers the simulated data under the private values model. Here, we find a (qualitatively inconsistent) decline in the persistence rate of 5.3 percentage points. As in our main specification, private-value estimates indicate that, after the reform, there is a improvement in Odense's screening accuracy and an increase in application costs. However, under private values an increase in application costs shrinks the applicant pool but does not enhance the quality of the selected applicant pool.

Next, we revisit the regression analysis outlined in equation (3) and present the DID coefficient and the "Prefer Odense effect" on persistence in rows 2 and 3 of Table 8. In the model with interdependent values, we find evidence for adverse selection at Aarhus among students who prefer Odense over Aarhus ($\alpha_1 < 0$). We also find some evidence that adverse selection worsens at Aarhus after the reform as shown by the negative DID coefficient. The interdependent values model estimate is directionally consistent with the evidence in the data, but the point estimate is much smaller in magnitude. We note that the confidence intervals around the point estimates can potentially account for a significant fraction of the difference in point estimates. Point estimates from the private values model do not indicate that persistence rates at Aarhus vary greatly with preferences for Odense (row 3), and suggest a slightly smaller negative DID effect than in the interdependent values model (row 2).

We next revisit the effect of the admission channel on persistence using the GPA RD cutoff design outlined in equation (1) in Panel B of Table 8. Both models can reconcile higher persistence rates among students admitted via quota 2 at the GPA cutoff, but the effect size of the model with interdependent values aligns closer in magnitude with the data.

Turning to self-selection, we revisit the specification outlined in Table 6 (column 4) and find that our main model can reconcile the advantageous selection among quota 2 applicants observed in the data (Panel C). This stands in contrast to the private values model that assumes that student preferences are independent of persistence outcomes.[21]

The next three rows in Panel D explore the relationship between the students' quota 2 rank percentile and persistence by program in the post-reform period. The estimates from the model with interdependent values suggest that Odense and Aarhus's ranking predict persistence to an extent that is consistent with the data. Our model also suggests that Aarhus' ranking predicts persistence, contrary to the point estimates from the data but to a lesser extent. We note that the model estimates fall into the 95% confidence interval of the data estimates. Estimates are similar for the private values model, which however seems to overstate the precision of Odense's signal, possibly because the private values model cannot account for changes in the student selection and hence attributes improvements in Odense's persistence rate after the reform to screening.

Finally, we revisit the correlation between program signals and student persistence. Consistent with the data and interdependent values, our main model suggests that Odense's signal predicts the persistence of students at Aarhus and Copenhagen conditional on Aarhus's signal. The private values model does not provide such a link between the signals of rival

[21] The "Interdependent Values" (IDV) and "Private Values" (PV) specifications in panel C of Table 8 use a different sample from their "data" analogue. In the data, the sample consists of students matched via quota 1. Both the IDV and PV models predict that a very small measure of students with GPAs above the cutoff will submit quota 2 applications, making it difficult to use this sample. We are able to use the models to simulate potential outcomes for all quota 1 applicants, however, not only those who matched to the program. Accordingly, for the "model" specifications, the sample consists of all quota 1 applicants to a program who are available to that program. Results are pooled across the three medical programs.

programs and instead overstates the predictive power of Aarhus's student ranking.

Table 8: Model Fit: Untargeted Moments on Student Persistence

Panel A: Information Experiment				
	Data		Interdependent Values	Private Values
Odense γ_{DID}	0.124***	(0.016)	0.055	-0.053
Aarhus, Prefer Odense $\times$ Post	-0.236***	(0.083)	-0.031	-0.023
Aarhus, Prefer Odense	0.059	(0.076)	-0.056	-0.012
Panel B: Q2 Admits at GPA Threshold				
γ_s	0.049***	(0.016)	0.045	0.036
Panel C: Selection of Q2 Applicants				
Applied Quota 2	0.035***	(0.012)	0.051	0.003
Panel D: Program Screening				
ODE rank percentile	-0.099***	(0.030)	-0.110	-0.175
AAR rank percentile	0.003	(0.041)	-0.062	-0.057
CPH rank percentile	-0.122***	(0.036)	-0.094	-0.105
Panel E: ODE's Rival Screening of AAR or CPH students				
ODE Ranks 1>2	0.073**	(0.034)	0.044	-0.009
AAR Ranks 1>2	-0.003	(0.034)	0.042	0.110

Note: This table presents reports untargeted data moments against simulated moments from the main model with interdependent values (column 3) and an alternative model with independent private values (column 4). The outcome variable in all panels is 3-year program persistence, conditional on being placed in the program. For data moments, we report coefficient estimates in the first column and standard errors in parentheses in the second column, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Panel A reports the difference-in-differences effects of Odense's information experiment on own student persistence (γ_{DID}) and on the performance of students at Aarhus, differentially for those who would have preferred Odense, analogous to Table 4. Panel B reports RD estimates γ_s for the persistence advantage of Q2 admits at the GPA threshold, analogous to Table 2. Panel C reports results for the persistence premium of quota 2 applicants who are admitted in Quota 1 without screening, analogous to Table 6. Panel D reports the relationship between each program's ranking of Q2 admits and their persistence, analogous to Table 3. Panel E reports results analogous to Table 5 for the difference in persistence of student pairs admitted at medical programs in Aarhus and Copenhagen but not at Odense.*

7.3 Program Signals, Preference Shocks, and Persistence

Figure 5 summarizes the estimated information structure of the game in the post-reform period, further detailed in Appendix Tables 27-22. For each program, we focus on available quota 2 students: those who would match the program if the program ranks them above its quota 2 cutoff. We plot the student's probability to persist on the vertical axis and a standardized signal, denoted in percentiles, on the horizontal axis.[22] For the purpose of this figure, we use data from a single post-period year, 2007. The vertical line denotes the quota

[22] We compute the distribution of $s_{ij} - x_i\beta_{j,\tau(t)}$, then report percentiles of this distribution. Recall that a student is admitted if $s_{ij} - x_i\beta_{j,\tau(t)}$ is greater than a year-specific cutoff $\beta^0_{j,t}$.

2 cutoff that we estimated in that year. Students to the right of the cutoff are admitted and matched to the program.

For each program, we consider three signal distributions. In this section, we do so while holding programs' cutoffs fixed, abstracting from equilibrium responses and from changes in cutoffs. An interpretation is that we consider the impact of changing one program's information about a specific student or a small measure of students.

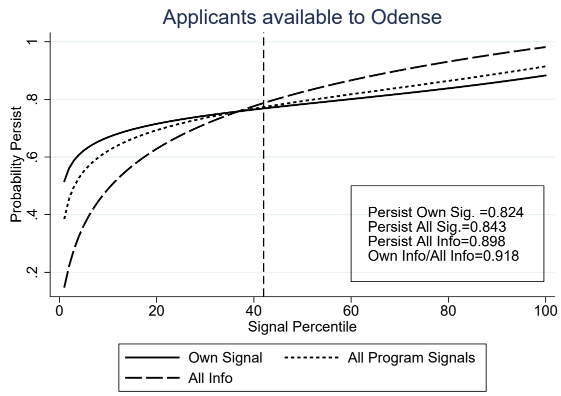
First, we consider the programs' own signal, denoted by the solid line. This curve is upward-sloping among admitted students for each program, indicating that program rankings positively correlate with the students' chances to persist. We report the average persistence among admitted students in the first row of the box in each graph, ranging from 69.2 percent at Aarhus to 82.4 percent at Odense (despite having the largest quota 2 admission share).

The second signal, denoted by the short-dashed lines, is the best linear predictor of program persistence based on all three program signals. Combining information from all programs would raise the average persistence rate among matched students, but differentially so across programs. As indicated in the second row of the box, the average persistence rate for a student "above the bar" under this alternative pooled signal would be 1.9 percentage points greater at Odense (from 82.4 to 84.3 percent) but about 5-8 percentage points greater at Aarhus and Copenhagen.

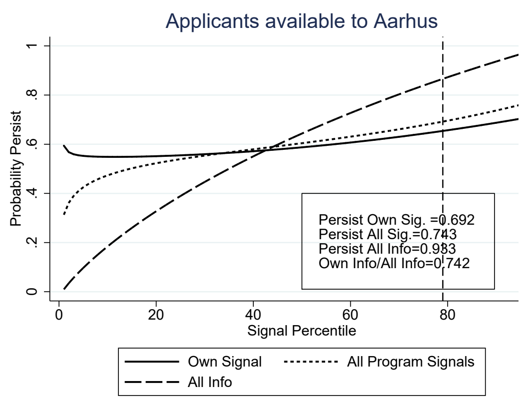
The third signal considers all information available to any agent including students themselves and is denoted by the long-dashed lines. Access to information held by students improves the average persistence rate among matched students further, but we again find differences across programs. As indicated in the third row of the box, the average persistence rate would increase by an additional 5.5 percentage points at Odense (from 84.3 to 89.8 percent). Copenhagen's and Aarhus' persistence rate would increase by an extra 7.8 and 24 percentage points, respectively.

The last row in the box presents the persistence ratio between each program's own signal and all information. We find that Odense has the least to gain from additional information, as indicated by a relatively high ratio of almost 92 percent. On the other hand, Aarhus has the lowest baseline persistence rate and the most to gain from access to other programs' or students' private information. Its students' persistence rate, 69.2%, is only 74.2 percent of the rate that could be achieved if it were able to observe all parties' private information.

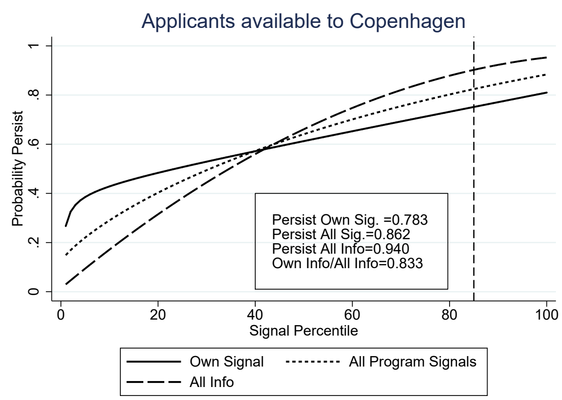
Figure 5: Signals and Persistence Among Available Q2 Applicants in Post-Reform Period



(a) Odense



(b) Aarhus



(c) Copenhagen

8 Counterfactuals

Figure 5 illustrates the importance of information frictions in our environment but abstracts away from strategic responses by applicants and programs to changes in the information structure. We consider these mechanisms in the following counterfactual analysis. We report averages over the post-reform period, solving for equilibrium in each post-reform year. We delegate further details to Appendix Section D. We focus our discussion on quota 2 students only as we find almost no changes among quota 1 students in most of the counterfactual analysis. We highlight effects on quota 1 students in the main text when they are present.

Our first counterfactual removes quota 2 application costs, so that everyone applies via quota 2 (and quota 1) to each program that is preferred over the outside option. While this benefits programs through a larger quota 2 applicant pool, it may also harm programs by undoing an initially advantageous selection of applicants. We find that the latter mechanism dominates at Odense, which has the highest application costs at baseline, see columns 1 and 2 in Table 9. This result suggests that the increase in Odense's application costs after the reform contributed to the positive reform effect on persistence. Aarhus, on the other hand, would benefit from the removal of application costs as high-quality students who can no longer signal their type to higher-cost programs are now admitted at Aarhus instead.

Table 9: Counterfactual Persistence Rates by Program

Program	CV Baseline	CV Free Q2 Apps	CV Full Info	CV View Top of List	PV baseline	PV Free Q2 Apps
Odense	0.838	0.800	0.912	0.838	0.795	0.850
Aarhus	0.754	0.778	0.979	0.748	0.750	0.662
Copenhagen	0.825	0.813	0.972	0.825	0.780	0.807

Note: This table presents counterfactual persistence rates among quota 2 admissions by program in the post-reform period. The first column presents baseline persistence rates in the estimated model with interdependent values (CV). Columns 2 and 3 subsequently remove quota 2 applicant costs before providing programs with on information on all program signals and applicant preference shocks. The last two columns present estimates for the private value model (PV) including the baseline persistence rate and counterfactual persistence rates after removing quota 2 application costs.

Next, we consider the case where applications are free and all signals and utilities are commonly observed. The difference between the baseline and this "full info" scenario quantifies the full cost of information frictions in terms of student outcomes. Our results suggest that the efficiency gains from full information are large; persistence would increase by 7 p.p. at Odense, 15 p.p. at Copenhagen, and 22 p.p. at Aarhus. Foreigners would lose out in this counterfactual, as their admission chances fall significantly, see Figure 13 for details.

Motivated by the importance of students' information in Figure 5, we also consider a "first preference" counterfactual in which programs observe and can condition on the student's first preference in their quota 2 admissions. While this may provide students an ability to share their excitement about the program, it may also encourage strategic application behavior. We find that students with stronger preferences for nonmedical programs (and lower persistence rates on average) misreport their preferences to boost their admission chances to medical programs, rendering the intervention largely ineffective (column 4).

Finally, we benchmark our findings to those obtained under a private value model. In the last two columns, we first display the estimated baseline persistence rates and then consider changes following the removal of application costs. Changes in persistence point in the opposing direction to those derived under our main model with interdependent values. Absent any advantageous selection of applicants, programs with higher application costs now benefit more because of larger increases in their applicant pools. Finally, we note that, by assumption, programs do not learn from rival signals or applicant preference shocks in the private value model. This implies that a full information counterfactual would leave the estimates from the last column unchanged.

9 Conclusion

In this paper we show that interdependent values exist in a matching market and matter for students' and programs' outcomes. We do so in the important context of Danish medical school admissions, providing new evidence and developing a novel model. Combining administrative data on students' preferences, programs' rankings of applicants, and students' outcomes, we show that students and rival programs hold payoff-relevant information that would, if known by a given program, allow that program to admit students with lower program dropout rates. We also demonstrate that programs adjust their admissions strategies to account for interdependent values, prioritizing local candidates who, reciprocally, show a preference for local programs. In doing so, they lower the risks of enrolling students previously rejected by other programs. Model estimates indicate that parties' pooling their private information could lead to substantial gains in students' persistence. However, we find that practical changes such as revealing candidates' first choices to programs, which might provide valuable information if students were to apply truthfully, do not raise persistence rates or improve match quality in equilibrium.

An alternative explanation for programs' "home bias" is statistical discrimination owing to differences in signal informativeness. If a program's evaluation is more indicative of the abilities of local students than of those in other regions, the program might find more local applicants that it believes have high ability. We find this explanation less applicable in our context, and therefore do not examine it, but it may be important in other settings.

While efforts to pool information could significantly improve persistence at medical programs, the focus of our analysis, the welfare implications for students of these policies are less clear-cut when students may learn about their preferences and match quality after enrollment (Larroucau et al., 2021). Learning about preferences may be less relevant in our setting, in which prospective students may have a better understanding of medical career profiles. Instead, the absence of academic readiness has been identified as a significant factor contributing to dropouts in our setting.

Despite the potential for considerable efficiency gains, our research indicates that improving market design in practice faces challenges. A key challenge is that the strategic behaviors of students may counteract the expected benefits of information sharing. In response, we plan to further investigate possible enhancements to market design in future research, focusing on the trade-offs between efficiency and equity that emerge.

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.

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.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995). "Automobile Prices in Market Equilibrium". *Econometrica: Journal of the Econometric Society*, pp. 841–890.

— (2004). "Differentiated products demand systems from a combination of micro and macro data: The new car market". *Journal of political Economy* 112.1, pp. 68–105.

Bjerre-Nielsen, Andreas and Emil Chrisander (2022). *Voluntary Information Disclosure in Centralized Matching: Efficiency Gains and Strategic Properties*. Working Paper. University of Copenhagen.

Board, Simon, Moritz Meyer-ter-Vehn, and Tomasz Sadzik (2017). *Recruiting talent*. Tech. rep. UCLA working paper.

Borghesan, Emilio (2022). *The Heterogeneous Effects of Changing SAT Requirements in Admissions: An Equilibrium Evaluation*. Tech. rep.

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.

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.

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., Chenyu Yang, and David H. Hsu (2018). "Unobserved Heterogeneity in Matching Games". *Journal of Political Economy* 126.4, pp. 1339–1373.

Friedrich, Benjamin (2023). *Information Frictions in the Market for Managerial Talent: Theory and Evidence*. Working Paper. Northwestern University.

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

Gandil, Mikkel and Edwin Leuven (Sept. 2022). *College admission as a screening and sorting device*. Memorandum. Oslo University, Department of Economics.

Genz, Alan (1992). "Numerical computation of multivariate normal probabilities". *Journal of computational and graphical statistics* 1.2, pp. 141–149.

Gourieroux, Christian, Alain Monfort, and Eric Renault (1993). "Indirect inference". *Journal of applied econometrics* 8.S1, S85–S118.

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.

Idoux, Clemence (2022). *Integrating New York City schools: The role of admission criteria and family preferences*. Tech. rep. MIT Department of Economics.

Kapor, Adam (2020). *Distributional effects of race-blind affirmative action*. Tech. rep.

Larroucau, Tomás, Manuel Martınez, Christopher Neilson, and Ignacio Rios (2021). *Application mistakes and information frictions in college admissions*. Tech. rep. Mimeo.

Larroucau, Tomás and Ignacio Rios (2020). *Dynamic college admissions and the determinants of students' college retention*. Working Paper.

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*, 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.

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

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

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 (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.

Somaini, Paulo (2020). "Identification in auction models with interdependent costs". *Journal of political Economy* 128.10, pp. 3820–3871.

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". *Quarterly Journal of Economics* 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.

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.

Online Appendix

A Appendix: Empirical Results

A.1 Details on Substitute Programs for Medicine

Program selection We define the market of applicants as applicants to either the three medical programs as Aarhus, Odense and Copenhagen or one of eight university-level programs that are popular among applicants to these medical schools. The close substitute programs are derived as follows: for applicants to each medical program, we list the top-three most frequent educational fields that the applicants also rank (excluding medicine and non-university level fields, e.g. nursing, as these are typically much less selective with many more schools offering the programs).

Applicants for the three medical programs commonly list the fields of dentistry and psychology as the two most popular university-level fields in addition to medical programs. Applicants to Aarhus medical school then list molecylar biomedicine as the third most popular field, where applicants to Odense and Copenhagen list clinical biomechanics and pharmacy, respectively. Programs in dentistry and psychology are offered at Copenhagen and Aarhus University only throughout the sample period. Aalborg University opened a psychology program in 1998, but University of Southern Denmark (Odense) did not open a similar program until 2010. Because empirics show that there is a considerable home bias in applicant preferences (see Table 1) we include clinical biomechanics as the third substitute field which is offered in Odense only throughout the sample period. Lastly, we add the Aalborg medical program as a substitute program to the medical programs in Aarhus, Odense, and Copenhagen. Consequently, the final list of substitute programs reads:

Programs	University	Program Years
Dentistry	Aarhus	1994-2013
Dentistry	Copenhagen	1994-2013
Psychology	Aarhus	1994-2013
Psychology	Copenhagen	1994-2013
Psychology	Aalborg	1998-2013
Psychology	Odense	2010-2013
Clinical biomedicine	Odense	1994-2013
Medicine	Aalborg	2010-2013

A.2 Applicant Preferences

Figure 6 presents evidence on student preferences, which organizes applicants in four distinct regions of residence: counties close to Odense, counties close to Aarhus, all other counties in Denmark, and foreign applicants.[23] Within each region, we display the share of applicants by five preference types. ”A” denotes that an applicant’s top priority among medical programs is Aarhus, and ”O” denotes a top priority for Odense. ”A2” and ”O2” denote preference rankings where an applicant lists Copenhagen (or Aalborg from 2010) 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.

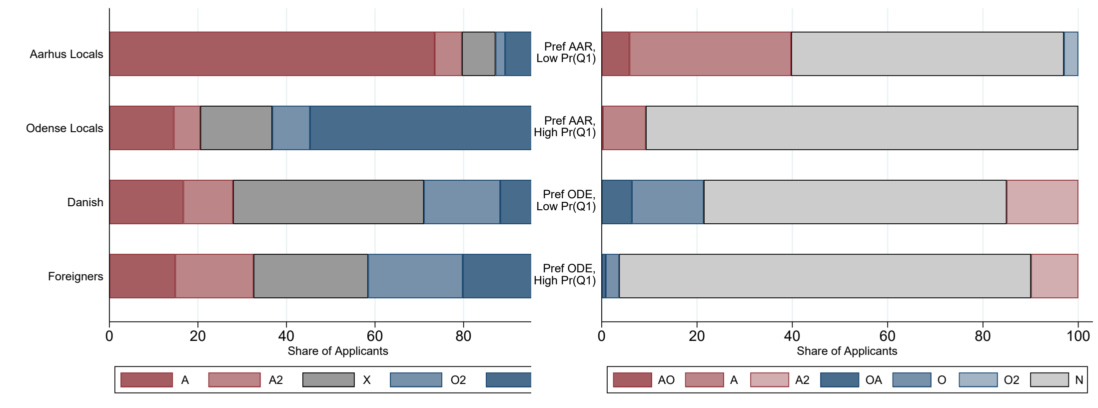
We note three insights from this figure. First, Copenhagen is most popular among applicants, but only in regions outside of Odense and Aarhus. Second, in counties close to Odense, Odense is the most popular program, whereas Aarhus is by far the most preferred program in counties close to Aarhus. In addition, 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.

Figure 6b 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 of at least 0.3 points above the maximum (high $Pr(Q1)$) and 0.3 points below the minimum (Low Pr(Q1)) of the GPA thresholds of 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 and these programs are not their preferred choice. “N” refers to students who only submit a quota 1 application.

This figure shows three key patterns. First, only a small share of applicants with high quota 1 admission probability (high Pr(Q1)) apply through quota 2, whereas students with a lower probability of quota 1 admission use quota 2 more frequently. Second, students are more likely to submit a quota 2 application at their preferred program. Third, quota 2 applications are more frequent at Aarhus, consistent with lower application costs than at Odense. Even applicants who prefer Odense frequently submit a quota 2 application at Aarhus, but not vice versa for students who prefer Aarhus.

[23]Counties near Aarhus include North Jutland, Aarhus, Vejle, and Viborg, while counties near Odense include Funen, Storstrom, West Zealand, and South Jutland, see Appendix E.1 for a map.

Figure 6: Program Preferences and Admission Chances by Residence

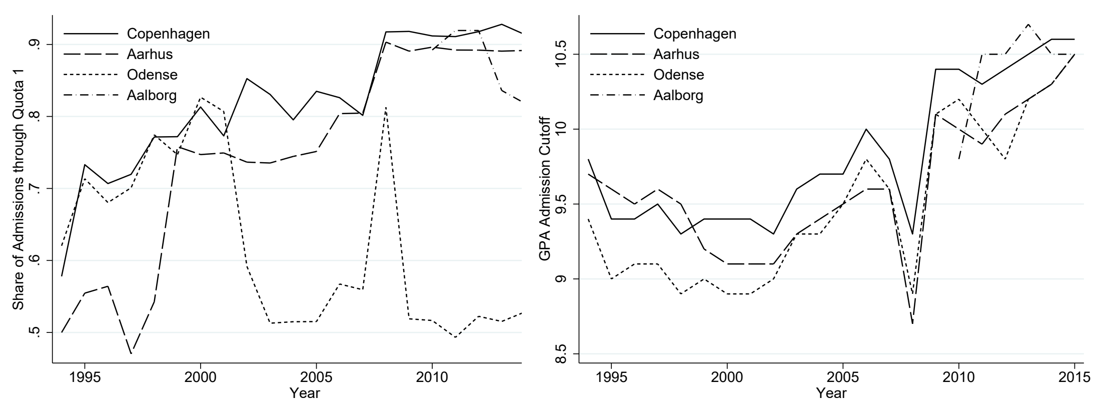


(a) Preferences by Former Residence (b) Quota 2 Applications

Note: Figure 6a plots the composition of applicant preferences by area of residency, see Appendix Section E.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 Copenhagen (or Aalborg from 2010) 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 6b 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))) between the GPA thresholds of 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 and these programs are not their preferred choice. "N" refers to students who only submit a quota 1 application.

A.3 Details on Admissions

Figure 7: Quota 1 Admissions and GPA Thresholds



(a) Quota 1 Admission Share (b) GPA Cutoff for Regular Admission

Notes: Data come from the Danish Central Admissions Secretariat (CAS). Figure 7a documents the share of quota 1 admissions out of all admissions by program and year. Figure 7b documents the quota 1 GPA cutoff by program over time, using a harmonized 7-point grading scale for all years.

Quota 1 Admissions Figure 7a documents the share of quota 1 admissions out of all admissions by program and year. Figure 7b documents the GPA admission thresholds for quota 1 on a unified scale, incorporating the transition from a 13-point to a 7-point scale in 2007. The quota 1 thresholds are inversely related to the quota 1 share, holding the applicant pool fixed. To put the magnitude of the GPA cutoff into perspective, see the distribution of high school GPA among medical school applicants in Figure 15c. 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 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 7a 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 in 2008, which reduced the number of valid applications, see Appendix E.2. Importantly, the extension was lifted again in 2009, reconciling the immediate increase in the GPA cutoffs.

A.3.1 Substitution Patterns

We assess the substitution patterns between medical school programs in Table 10. We document that most students applying to Odense also apply to Aarhus (69%) and Copenhagen (66%). However, due to the high popularity of Copenhagen's medical school program and its competitive admission standards, only 0.7% of rejected students at Odense are admitted to Copenhagen, reducing the potential importance of a winner's curse. This share increases more than threefold to 2.7% when considering those admitted to Aarhus. Similarly, about 4.3% of the students admitted 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. These shares are substantially larger than the fraction of applicants who list Copenhagen next (20 and 21% among applicants who prefer Odense and Aarhus, respectively).

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

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

A.3.2 Admitted Quota 1 and Quota 2 Applicants

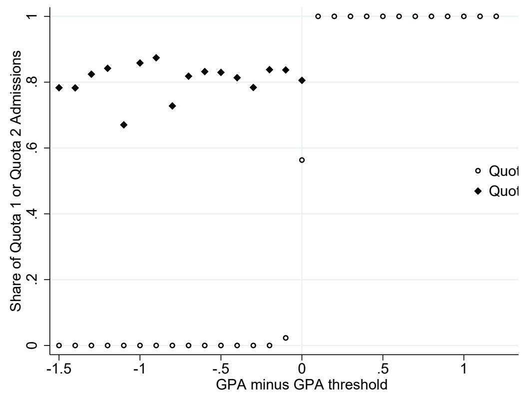
Figure 8 complements the evidence in Figure 1 and Table 2. The evidence in the left panel shows the discontinuity in admission chances at the GPA threshold. In addition, Quota 2 admission chances increase substantially with GPA at Aarhus, but are constant across a wide GPA range at Odense and Copenhagen. Programs further differ in the level probability of Quota 2 admissions. The right panel of Figure 8 shows the discontinuity in dropout rates at the GPA threshold separately by program. Interestingly, dropout rates are constant across students with different GPA admitted through Quota 2 at Odense, whereas dropout rates increase steeply for low GPA students admitted via Quota 2 at Aarhus.

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

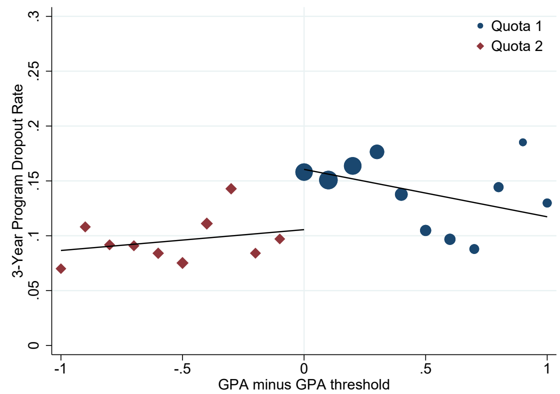
$$\begin{aligned} Y_{ijt} &= \gamma_0 + \gamma_{gpa_{q1}} \cdot gpa_i \cdot \mathbb{1}\{GPA \geq cutoff\} + \gamma_{gpa_{q2}} \cdot gpa_i \cdot \mathbb{1}\{GPA < cutoff\} \\ &+ \gamma_s \cdot \mathbb{1}\{GPA < cutoff\} + \gamma_{jt} + \epsilon_{ijt}, \end{aligned} \tag{9}$$

where we control for differential linear trends in gpa to the left and right of the GPA cutoff.

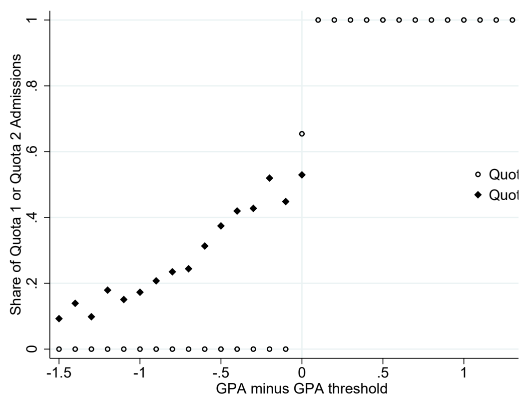
Figure 8: Admissions and Dropouts by Quota



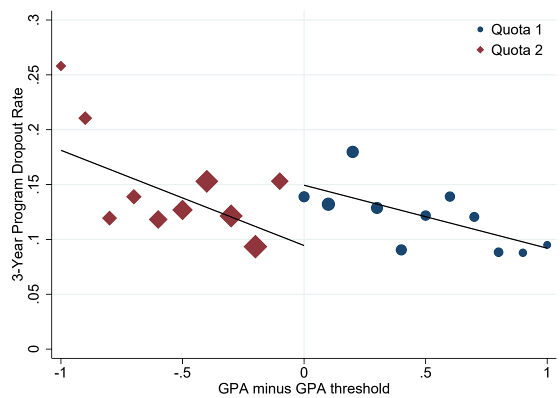
(a) Admissions by GPA: Odense



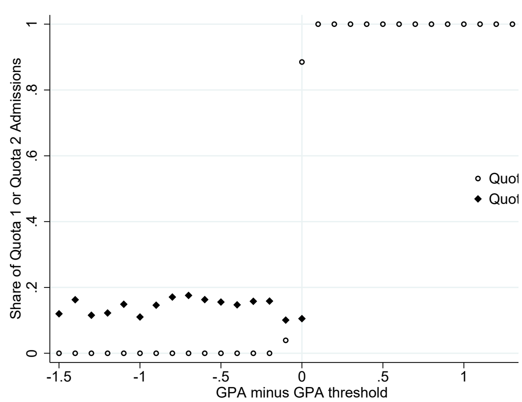
(b) Dropouts by GPA: Odense



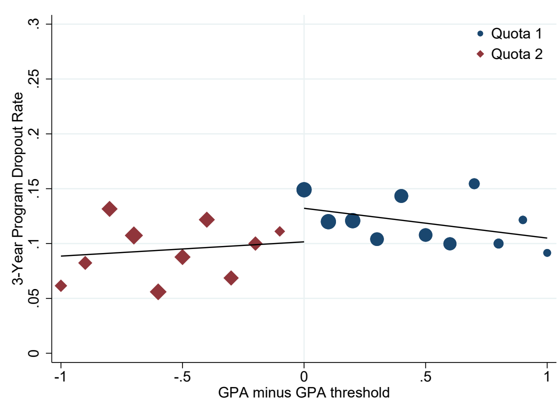
(c) Admissions by GPA: Aarhus



(d) Dropouts by GPA: Aarhus



(e) Admissions by GPA: Copenhagen



(f) Dropouts by GPA: Copenhagen

Note: Figures 8a, 8c, and 8e plot the fraction of admitted among available applicants to Odense, Aarhus, and Copenhagen by quota as a function of the difference between the student's GPA and the program's quota-1 GPA cutoff, in grade-points. Figures 8b, 8d, and 8f maintain the same horizontal axis but plot the 3-year dropout rate on the vertical axis for students enrolled in each program, respectively. This figure omits students admitted via quota 1 (quota 2) whose GPA is below (above) the GPA cutoff. The lines show the best linear fit of dropouts on GPA among quota 1 and quota 2 enrollees, weighted by the number of observations in each bin.

Table 11: Programs' Information Quality and Student Persistence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1Y Dropout		3Y Dropout		Completion		Time to Complete	
γ_s	-0.030***	-0.019*	-0.052***	-0.027*	0.071***	0.053***	-43.842**	-27.957
	(0.009)	(0.010)	(0.013)	(0.016)	(0.016)	(0.020)	(17.545)	(21.877)
$\gamma_{gpa_{q1}}$	-0.000	0.000	-0.003***	-0.001	0.004***	0.000	-1.837	-7.607**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(1.552)	(3.786)
$\gamma_{gpa_{q2}}$	-0.001	-0.000	-0.002	-0.002	0.006**	0.006**	-5.148*	-4.390
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(2.890)	(2.930)
Constant	0.112***	0.069**	0.266***	0.189***	0.783***	0.786***	2,745.9***	2,623.3***
	(0.019)	(0.027)	(0.028)	(0.043)	(0.031)	(0.049)	(35.77)	(55.34)
Sample	Q1+Q2	Q2	Q1+Q2	Q2	Q1+Q2	Q2	Q1+Q2	Q2
Observations	15,554	5,842	15,554	5,842	11,476	4,728	9,633	3,994
R-squared	0.009	0.011	0.014	0.016	0.011	0.018	0.088	0.119

*Note: This table presents estimates from regression model (1). Odd columns include all enrolled students. Even columns include only students who have applied to their study program via quota 2. Columns 1-2 (3-4) consider the one-year (three-year) dropout rate among enrolled students. Column 5-6 and 7-8 analyze completion rate and time until completion among graduates, respectively. All columns pool enrolled students at all three institutions, and include program-by-year fixed effects. Standard errors are reported in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

The key parameter of interest is γ_s, which denotes the discontinuous change in the outcome measure when going from quota 1 to quota 2. Graphically, this corresponds to going from the right of the cutoff to the left of the cutoff in Figures 1b and 8b, 8d, and 8f.

We revisit the main findings from Table 2 in various robustness exercises, which we summarize in Table 11. Odd columns include all enrolled students within a 1-point GPA band from the GPA threshold in their respective program, analogous to Table 2. We show that the discontinuity is robust to using the 1-year dropout rate or overall completion rates for cohorts 1994–2009 as alternative outcome measures. The difference in 1-year dropout rates at the GPA threshold equals 3 percentage points, and we find 7.1 percentage points differences in total completion. In addition, column 7 of Table 11 shows that students admitted through Quota 2 take less time (44 days) to complete their studies on average.

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

A.3.3 Program Ranking and Dropout Outcomes

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

Figure 9 complements Figure 2a in the main text and illustrates the relationship between student ranking (based on program screening among quota 2 admitted and high school GPA among quota 1 admitted students) and dropout rates separately by medical program. These figures reveal substantial differences: While Copenhagen and Odense extract and act on dropout-relevant information in their quota 2 rankings, the ranking at Aarhus is not predictive of dropouts among quota 2 students.

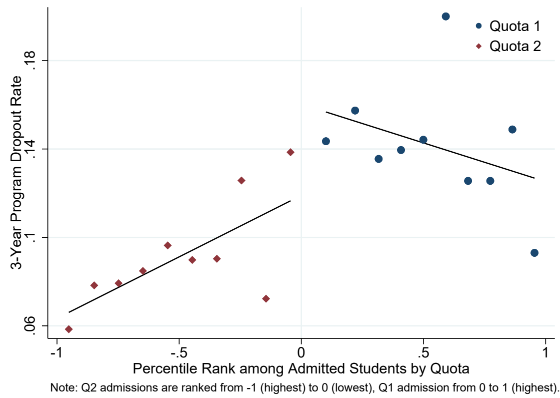
We formalize these findings in Table 12 by estimating the differences in dropout rates among enrolled students at each program according to their position on the program's ranking for admissions. To also compare marginal students admitted through Quota 1 and Quota 2, we estimate regression-discontinuity models,

$$\begin{aligned} Y_{ijt} &= \gamma_0 + \gamma_{perc_{q1}} \cdot (1 - perc_i) \cdot \mathbb{1}\{Q1adm\} + \gamma_{perc_{q2}} \cdot (perc_i - 1) \cdot \mathbb{1}\{Q2adm\} \\ &+ \gamma_s \cdot \mathbb{1}\{Q2adm\} + \gamma_{jt} + \epsilon_{ijt}, \end{aligned} \tag{10}$$

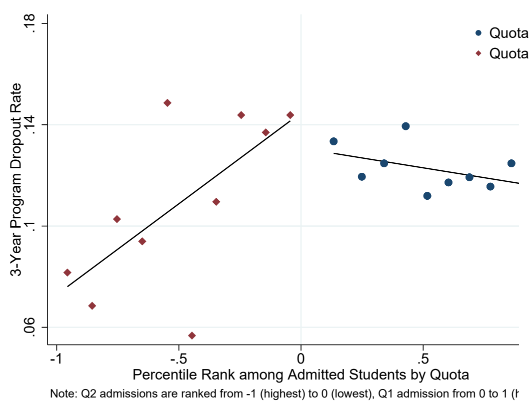
where $perc_i \in [0, 1]$ is the percentile rank of student i in their admission quota. We control for linear trends in the rankings for Quota 1 and Quota 2 students. The key parameter of interest is γ_s, which denotes the discontinuous change in dropout rates when going from quota 1 to quota 2. Graphically, this corresponds to going from the right of the cutoff to the left of the cutoff at 0 in Figure 9. Note that we rescale the percentiles such that the order is from best to worst among Quota 2 students, but from worst to best among Quota 1 students.

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

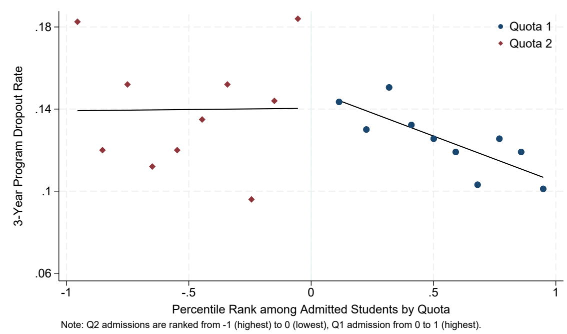
Figure 9: Dropouts by Rank within Quota



(a) Odense



(b) Copenhagen



(c) Aarhus

Note: This figure plots the 3-year dropout rate among enrolled students as a function of the student's percentile rank in their corresponding admission quota. The reported quota 2 ranking is flipped ranging from -1 for the highest-ranked admitted student to 0 for the lowest-ranked student. In contrast, the reported quota 1 ranking ranges from 0 for the student with the lowest GPA admitted through quota 1 to 1 for the student with the highest GPA. We split students into 10 equally sized bins (deciles) within each quota. Lines show the best linear fit. Observations are reported separately for each program. Blue and red data points correspond to students admitted via quota 1 and quota 2, respectively.

Table 13 supplements Table 5 in the main text by analyzing the relative assessments of quota 2 applicants to both Copenhagen and Odense in Panel A, and to all three focal programs (Aarhus, Copenhagen, Odense) in Panel B. While the sample shrinks substantially in Panel B when selecting only applicants who submit three quota 2 applications, the qualitative patterns of the results are similar across panels and confirm the evidence in the main text. Conditional on rivals' signals, Odense's ranking of applicants is highly predictive of their study success. We also find evidence of informative signals at Copenhagen conditional on Odense's assessment, but their signal precision seems to be particularly strong in the period

Table 12: Student Persistence for Marginal Q1 and Q2 Admissions

	(1) Pooled	(2) Aarhus	(3) Odense	(4) Copenhagen
γ_s	-0.013	-0.009	-0.036	0.003
	(0.012)	(0.022)	(0.022)	(0.020)
$\gamma_{perc_{q1}}$	-0.032***	-0.045**	-0.039	-0.017
	(0.011)	(0.019)	(0.026)	(0.017)
$\gamma_{perc_{q2}}$	0.048***	0.016	0.052*	0.071**
	(0.017)	(0.033)	(0.027)	(0.029)
Constant	0.262***	0.127***	0.146***	0.122***
	(0.029)	(0.020)	(0.024)	(0.019)
Observations	16,436	5,708	3,815	6,913
R-squared	0.013	0.005	0.031	0.012

*Note: This table presents estimates from regression model (10) for the 3-year program-specific dropout rate. The first row presents γ_s, rows 2 and 3 present $\gamma_{perc_{q1}}$ and $\gamma_{perc_{q2}}$. Column 1 presents pooled results for students enrolled in medicine at Copenhagen, Aarhus or Odense. Column 2-4 consider outcomes at each medical program separately. All regressions control for program-by-year fixed effects. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

pre-2002 and weakens substantially after 2002 when Odense's screening reform helps them to extract more precise information.

A.4 More on Odense's Admission Reform

In this section, we conduct robustness tests for the results in Table 4 and Figure 3. First, Table 14 provides additional results complementing Table 4. Columns 2 and 4 are replicated from Table 4 for ease of comparison. Similarly, we document a 4.1 (3.3) p.p. reduction in the one-year program (medical) dropout rates in column 1 (column 3), as well as a 4 p.p. increase in completion rates in column 5, and a reduction in the time to completion by 109 days on average among cohorts first enrolling 1994-2009 in column 6.

Figure 10 provides robustness for the results in Figure 3. While Figure 10a replicates the result on 3-year dropout rates at Odense from the main text, Figure 10b provides analogous results when excluding transfers to other medical schools as dropouts. Figures 10c and 10d 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. Some of the fluctuations in the 1990s may also have been caused by the generous availability of study grants, incentivizing some low-performing students to remain enrolled even if they ultimately intended to drop out of the program. 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

Table 13: Quota 2 Ranking and Student Dropout Rates: Pairwise Comparisons

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	ODE 1>2	Difference in 3Y Dropout for Student 1 versus Student 2				
Panel A: ODE and CPH	All Both ranked	All Both enrolled	Both ODE Both Enrolled	None ODE Both enrolled	Pre-2002 Both enrolled	Post-2002 Both enrolled
ODE Ranks 1>2		-0.090***	-0.008	-0.065***	-0.052**	-0.096***
		(0.015)	(0.017)	(0.023)	(0.024)	(0.017)
CPH Ranks 1>2	0.100***	-0.054***	-0.026	-0.088***	-0.129***	-0.039**
	(0.013)	(0.014)	(0.016)	(0.023)	(0.033)	(0.016)
Observations	118,735	106,270	33,923	21,960	16,986	89,284
R-squared	0.037	0.053	0.066	0.104	0.123	0.055
Panel B: ODE, AAR and CPH	All Both ranked	All Both enrolled	Both ODE Both Enrolled	None ODE Both enrolled	Pre-2002 Both enrolled	Post-2002 Both enrolled
ODE Ranks 1>2		-0.120***	-0.030	-0.072**	-0.044	-0.129***
		(0.021)	(0.020)	(0.033)	(0.037)	(0.022)
AAR Ranks 1>2	0.056***	-0.013	-0.023	-0.011	0.010	-0.018
	(0.020)	(0.017)	(0.016)	(0.032)	(0.031)	(0.019)
CPH Ranks 1>2	0.074***	-0.037*	-0.032	-0.054*	-0.100**	-0.026
	(0.019)	(0.019)	(0.021)	(0.032)	(0.049)	(0.020)
Observations	39,687	36,557	12,862	7,221	3,991	32,565
R-squared	0.056	0.087	0.102	0.142	0.194	0.096

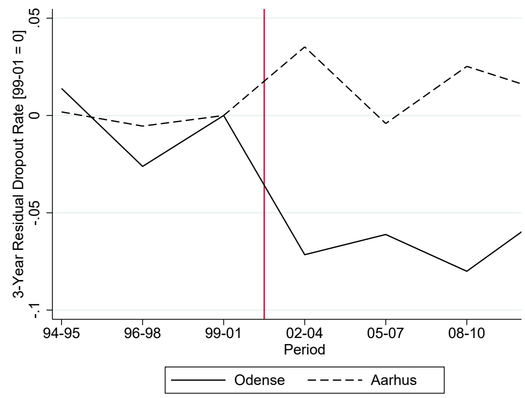
*Note: Panel A of Table 5 analyzes Copenhagen's and Odense's relative quota 2 rankings for pairs of quota 2 applicants to both programs, while Panel B analyzes pairs of quota 2 applicants to Copenhagen, Aarhus, and Odense. "ODE Ranks 1>2" is an indicator variable that takes value 1 if Odense assigns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

rates after the screening reform, see Figure 10d.

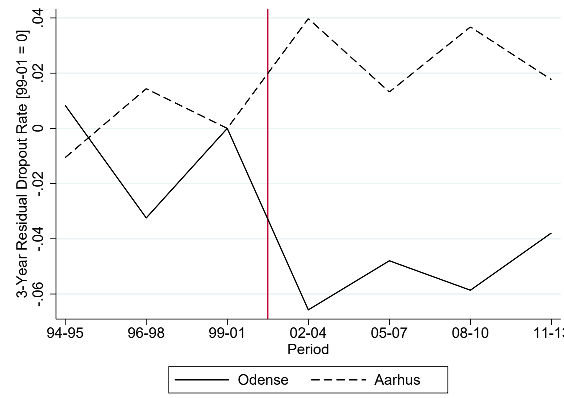
A.5 Details on Self-Selection and Quota 2 Admissions

Figure 11 provides details on programs' preferences in quota 2 admissions based on their rankings. All results analyze residual preferences by applicants' former region of residence, controlling for GPA-year fixed effects. Figure 11b analyzes the probability of quota 2 admission. The evidence further supports Odense's reduction in home bias and Aarhus' shift towards foreign applicants. Figure 11a repeats the analysis from Figure 2b for the pre-reform period, splitting the relevant applicant pool at each program into two subgroups based on their rank in the top half or bottom half of the program's list. The evidence suggests more limited strategic considerations for quota-2 rankings among the better quota-2 applicants using the pre-reform period when Aarhus had a large number of quota 2 seats. This is consistent with fewer strategic considerations for top students.

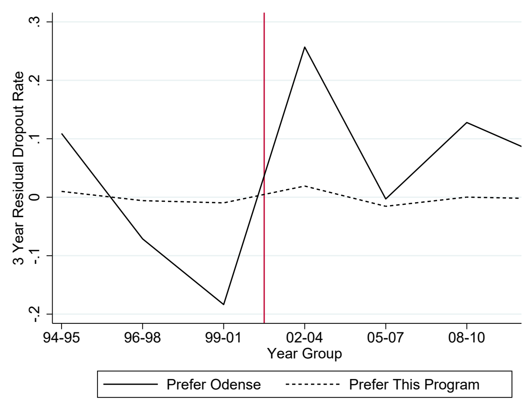
Figure 10: Dropout Rates by Medical Program Over Time



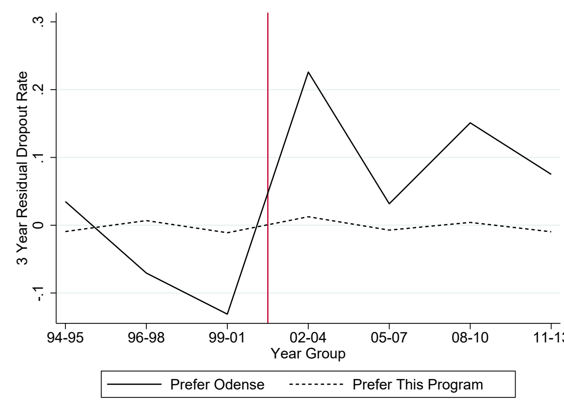
(a) Program-Specific 3-Year Dropout



(b) Any 3-Year Dropout (incl. transfers)



(c) Program-Specific 3-Year Dropout



(d) Any 3-Year Dropout (incl. transfers)

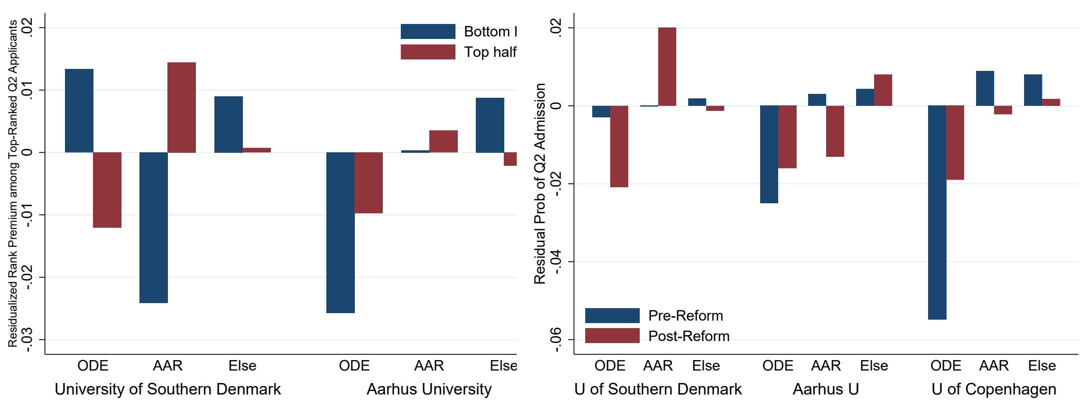
Note: Figures 10a and 10c plot the program-specific 3-year dropout rate of enrolled students to Aarhus and Odense over time, while Figure 10b and 10d measure all dropouts, including transfers within the first three years of study or before the first BA degree, whichever comes first. The vertical axis in each graph reports average residual dropout rates after controlling for year and GPA FE. The vertical lines denote the screening reform in Odense in 2002. Figures 10c and 10d focus on students enrolled at Aarhus University and distinguish students who preferred Aarhus or Odense on their application ranking.

Table 14: Student Persistence at Odense and the Admission Reform

	(1)	(2)	(3)	(4)	(5)	(6)
	Prog 1y	Prog 3y	Med 1y	Med 3y	Completion	Study Time
γ_{DID}	-0.041***	-0.071***	-0.033***	-0.045***	0.040**	-109.528***
	(0.010)	(0.015)	(0.010)	(0.014)	(0.018)	(19.459)
Constant	0.058***	0.135***	0.053***	0.121***	0.832***	2,605.410***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(4.274)
Observations	18,114	18,114	18,114	18,114	13,403	11,198
R-squared	0.038	0.049	0.037	0.047	0.054	0.140

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

Figure 11: Programs' Preferences and Quota 2 Admissions



(a) Q2 Adm Ranks by Location: Pre-2002 (b) Prob of Admission (above the bar)

Note: ODE (AAR) denotes applicants from counties close to Odense (Aarhus) in the year before application. "Else" pool former residents of the remaining counties and foreign applicants, see Appendix E.1. Figure 11a presents the average rank of quota 2 applicants after controlling for year-GPA fixed effects. Figure 11a plots the pre-reform years only for applicants ranked just below and up to 2 times the available number of quota 2 seats, and split the applicants by being ranked in the top (i.e. rankings 1-1.5 times the the available seats) vs. bottom half (1.5-2 times the available seats) of the applicant pool. Figure 11b plots the average probability of being ranked above the quota 2 threshold by former region of residence, after controlling for year-GPA fixed effects.

B Appendix: Model

B.1 Primitive Conditions for Cutoff Strategies

We provide a statistical assumption that ensures that programs employ cutoff strategies, admitting students with signals above an X-specific cutoff value.

Let $P(D_{j2}(x)|\omega_j, s_j)$ ($P(D_{j2}(x)|s_j)$) denote the probability of set of available students $D_{j2}(x)$ conditional on (ω_j, s_j) (s_j), where we omit D_{j2}'s dependence on $(\underline{r}, \ell, a, r)$ for brevity.

Define the density

$$g_j(\omega_j|s_j; D_{j2}(x)) = \frac{P(D_{j2}(x)|\omega_j, s_j) \cdot f(\omega_j|s_j)}{P(D_{j2}(x)|s_j)}.$$

We say that a density $\hat{g}$ first-order stochastically dominates (FOSD) a density $\tilde{g}$ if the random variables with the corresponding densities do.

Assumption 3 *The density $g_j(\cdot|s_j; D_{j2}(x))$ first order stochastically dominates $g_j(\cdot|s'_j; D_{j2}(x))$ for all signals s_j, s'_j with $s_j > s'_j$.*

Proposition 1 *Under Assumptions 1 and 3, program j's quota-2 ranking function $r^2_j(s_j, x)$ is increasing in s_j for all x, for each j. Moreover, there exist program-specific cutoff functions $\underline{s}_j(x)$ such that $r^2_j(\underline{s}_j(x), x) = \underline{r}^2_j$. Students of type x match to pseudoprogram $(j, 2)$ if and only if they belong to $D_{j2}(x)$ and have $s_j \geq \underline{s}_j(x)$.*

Proof. School j's payoff from a student with signal s_j can be written as

$$\pi(s_j) = \frac{1}{P(D_{j2}(x)|s_j)} \cdot \int_{\mathbb{R}} \int_{D_{j2}(x)} \omega_j \, dF(y|\omega_j, s_j) \, dF(\omega_j|s_j) = \frac{1}{P(D_{j2}(x)|s_j)} \cdot \int_{\mathbb{R}} P(D_{j2}(x)|\omega_j, s_j) \cdot \omega_j \, dF(\omega_j|s_j),$$

where $y = (\omega_{-j}, s_{-j}, u, c)$. Hence, if $g_j(\cdot|s_j; D_{j2}(x))$ first order stochastically dominates $g_j(\cdot|s'_j; D_{j2}(x))$ for every signals s_j, s'_j with $s_j > s'_j$, then $\pi(s_j)$ is increasing in j.

■

Assumption 3 is an assumption on an endogenous object. It can be verified, given parameters and cutoffs. However, one may wish to have primitive conditions that hold for all parameter values. The following two assumptions on primitives imply Assumption 3, and hence ensure that Proposition 1 holds.

Assumption 4 (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 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 5 (MLRP) *For all x, for $j = 1, 2, 3$, 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 $s'_j > s_j$.*

Under Assumptions 4 and 5 we can write

$$g_j(\omega_j|s_j; D_{j2}(x)) = \frac{P(D_{j2}(x)|\omega_j) \cdot f(\omega_j|s_j)}{P(D_{j2}(x)|s_j)},$$

and, by Assumption 5, if (ω_j, s_j) have joint density $g_j(\omega_j|s_j; D_{j2}(x))$ they are affiliated (Milgrom and Weber, 1982), which implies the FOSD condition in Proposition 1. Hence, we obtain:

Corollary 1 *Under Assumptions 1, 4 and 5 there is an equilibrium in which the programs' quota-2 student rankings increase in the students' signals.*

C Appendix: Estimation

C.1 Estimation Step 1: Primitives and Cutoffs

A history is a list of exogenous observables and all observable endogenous choices and outcomes:

$$X := ((GPA, Location, Year), \text{Q1app}, \text{Q2app}, \text{Q2offer}, \text{Q2top50\%}, \text{Match Program}, \\ \text{Match Quota}, \text{Persist}),$$

where Q1app is the quota 1 rank-ordered list which may be any ordering of any subset of $(1, 2, 3, 4)$, Q2app $\in \{0, 1\}^3$ indicates quota 2 applications, Q2offer $\in \{0, 1\}^3$ indicates whether the student is above the quota 2 cutoff in each school, Q2top50% $\in \{0,1\}^3$ indicates whether the student is in the top 50% of students who received offers,[24] Match Program $\in \{0,1,2,3,4\}$ indicates the program to which the student was matched, Match Quota $\in \{1,2\}$ is the quota through which the student matched,[25] and Persist $\in \{0,1\}$ is equal to 1 if the student was matched to some $j \in \{1,2,3\}$ and is enrolled in the matched program three years later. The observables X are divided into 734 cells consisting of location, year, and fine GPA bins, each of which has $23,883$ possible sequences of endogenous outcomes.[26] Considering each feasible list of endogenous outcomes at each value of X, we have $17,530,122$ total histories.

Our goal is to find parameters and cutoffs that match the model-predicted distribution over histories to the distribution of histories found in the data. To do so, we construct three types of moments. "Probit" moments minimize the distance between utility-index parameters γ and the coefficients of probit specifications for applying to program j via quota 1 estimated on the data. "LPM" moments match coefficients in linear regressions estimated in the data to analogous regressions on model output. "Outcome" moments match model-predicted and observed shares of outcomes such as offers or persistence rates by program, quota, and year, or by program, period, year, and location. We include separate "Probit" and "LPM" moments for the pre-reform and post-reform periods.

Formally, our estimator solves the following minimization problem:

$$\min_{\theta,\underline{s},\overline{s}} g(\theta,\underline{s},\overline{s})' W g(\theta,\underline{s},\overline{s}) \tag{11}$$

$$\text{where } g(\theta,\underline{s},\overline{s}) = [g^{\text{Probit}}, g^{LPM}, g^{\text{Outcome}}](\theta,\underline{s},\overline{s}) \tag{12}$$

$$\underline{s}_{j,t}(x) = \beta^0_{j,t} + x\beta^x_j, \;\; \overline{s}_{j,t}(x) = \beta^{0,\text{safe}}_{j,t} + \beta^0_{j,t} + x\beta^x_j \;\; \forall x, \; j. \tag{13}$$

The parameter vector θ consists of persistence parameters α, cutoff parameters (β^0, β), utility parameters γ, application costs δ, and the parameters governing the covariance of talents, signals, and utilities. The matrix W is a positive definite matrix. The cutoff $\underline{s}_{j,t}(x)$ is the minimum signal needed to be ranked "above the bar" at program j in year t for students with observables x. Similarly, $\overline{s}_{j,t}(x) = \underline{s}_{j,t}(x) + \beta^{0,\text{safe}}_{j,t}$ is the minimum signal needed

[24]Suppose the lowest-ranked quota 2 applicant to program j in year t who received an offer from j was ranked N_{j2t} on j's rank-order list that year. Then Q2offer$_j$ $= 1$ for quota 2 applicants to j in t that the program ranked N_{j2t} or better, and Q2top50%$_j$ $= 1$ for applicants ranked $N_{j2t}/2$ or better.

[25]In the event the student was not matched to any program, we adopt the convention Match Program $= 0$ and Match Quota $= 1$

[26]We omit infeasible histories. E.g. one cannot receive a "top 50%" offer without receiving an offer.

to be ranked among the top half of students receiving an offer. Parametric restrictions are motivated by limited data. With more data, one could in principle estimate cutoffs nonparametrically.

For our GMM objective, we choose a diagonal weight matrix W with weights proportional to the inverse variance of each moment in the data. We provide a full set of moments, and present in-sample fit, in Tables 28 through 38. We next provide additional details on the auxiliary Probit and LPM specifications.

In principle one could conduct first-step estimation via maximum likelihood. Computational constraints on the secure server, and privacy constraints which prohibit exporting microdata, motivate our use of GMM.

C.1.1 Indirect Inference: Auxiliary Regression Models

The indirect inference part of our estimation approach aims to match Probit models for quota 1 applications, as well as several linear probability and regression models of admission and persistence outcomes, separately for each program and the PRE and POST period.

We model each outcome as a function of observable characteristics x and endogenous outcomes observed at that time. Observable characteristics x include a constant, high school GPA, and location fixed effects for former residency in counties close to Aarhus, Odense, other parts of Denmark, or Foreign.

First, we target Probit models for quota 1 applications to medical programs in Aarhus, Odense, and Copenhagen in the pre-reform ($\tau = 0$) and post-refotm ($\tau = 1$) periods. For each of these options k, the Probit specification is

$$P(Q1app_j = 1|X, \tau) = \Phi\left(\tilde{\gamma}_{j\tau}X\right) \tag{14}$$

Matching these moments with the model does not require computing it. By assumption we have $Q1app_{ij} = 1(X_i\gamma_{j\tau(t(i))} + \varepsilon_{ij} > 0)$, with

$$\varepsilon_{ij} = \rho^0_{\varepsilon_{j\tau}}\tilde{\varepsilon}_{i0t} + \tilde{\varepsilon}_{ijt} \sim N(0, \rho^0_{\varepsilon_{j\tau}} + 1).$$

We therefore have:

$$P\left(app^k_{it} = 1|X\right) = \Phi\left(\frac{\gamma_{j\tau}}{\sqrt{\rho^0_{\varepsilon_{j\tau}} + 1}}X\right).$$

Let θ denote the vector of parameters, including preference parameters $\rho^0_{\varepsilon_{j\tau}}$ and $\gamma_{j\tau}$. Probit moments are given by

$$g^{\text{probit}}(\theta)_{j,\tau} = ||\gamma_{j\tau} - \tilde{\gamma}_{j\tau}\sqrt{\rho^0_{\varepsilon_{j\tau}} + 1}||. \tag{15}$$

Second, we target the preference for applying to programs other than the Aarhus, Odense and Copenhagen medical programs on the platform. We measure this preference as the number of medical programs that an applicant lists higher than the first non-medical program or the outside option, n_{med}, and target a linear regression for this measure,

$$\begin{aligned}
n_{med} = \tilde{\gamma}_0^{nm} + \sum_l \tilde{\gamma}_l^{nm} \mathbb{1}\left\{loc_i = l\right\} + \tilde{\gamma}_{gpa}^{nm} GPA_{it} \\
+ \tilde{\gamma}_a^{nm} \mathbb{1}\left\{app_{it}^{aar}\right\} \mathbb{1}\left\{app_{it}^{ode} = 0\right\} + \tilde{\gamma}_o^{nm} \mathbb{1}\left\{app_{it}^{ode}\right\} \mathbb{1}\left\{app_{it}^{aar} = 0\right\} \\
+ \tilde{\gamma}_{ao}^{nm} \mathbb{1}\left\{app_{it}^{ode}\right\} \mathbb{1}\left\{app_{it}^{aar}\right\} \mathbb{1}\left\{AAR \succ ODE\right\} \\
+ \tilde{\gamma}_{oa}^{nm} \mathbb{1}\left\{app_{it}^{ode}\right\} \mathbb{1}\left\{app_{it}^{aar}\right\} \mathbb{1}\left\{ODE \succ AAR\right\} \\
+ \tilde{\gamma}_c^{nm} \mathbb{1}\left\{app_{it}^{cph}\right\} + \tilde{\gamma}_{c1}^{nm} \mathbb{1}\left\{app_{it}^{cph}\right\} \mathbb{1}\left\{r(cph) = 1\right\} + \tilde{\gamma}_{c2}^{nm} \mathbb{1}\left\{app_{it}^{cph}\right\} \mathbb{1}\left\{r(cph) = 2\right\}
\end{aligned} \tag{16}$$

Third, we use linear probability models to match the probability of quota 2 application y_{ijt}^{q2} among quota applicants for each program j. For each j, we include controls for the preference ranking between program j and both alternative medical programs, as well as the quota admission outcomes at the two rival programs (in case the applicant applied there as well).

$$\begin{aligned}
\mathbb{1}\left\{y_{ijt}^{q2}\right\} = \tilde{\gamma}_{j0}^{q2} + \tilde{\gamma}_{j1}^{q2} GPA_{it} + \sum_l \tilde{\gamma}_{jl}^{q2} \mathbb{1}\left\{loc_i = l\right\} + \tilde{\gamma}_{jn1}^{q2} \mathbb{1}\left\{NM \succ j\right\} \\
+ \sum_{j' \in ODE, AAR, CPH} \mathbb{1}\left\{j' \neq j\right\} \left(\tilde{\gamma}_{juj'}^{q2} \mathbb{1}\left\{y_{i,j',t}^{q1}\right\} + \tilde{\gamma}_{jcj'}^{q2} \mathbb{1}\left\{y_{i,j',t}^{q2}\right\}\right) \\
+ \sum_{j' \in ODE, AAR, CPH} \mathbb{1}\left\{j' \neq j\right\} \left(\tilde{\gamma}_{jpj'}^{q2} \mathbb{1}\left\{(j \succ j')_{it}\right\} + \tilde{\gamma}_{jqj'}^{q2} \mathbb{1}\left\{y_{i,j',t}^{q2} * (j \succ j')_{it}\right\}\right) + \epsilon_{ijt}^{q2}
\end{aligned} \tag{17}$$

Fourth, we use linear probability models to match the probability of receiving a potential offer adm_{ijt}^{q2}, indicating whether the candidate is above the bar for quota 2 at program k, among quota 2 applicants for each program k. For each k, we include controls for the preference ranking between program k and both alternative medical programs, as well as the quota 2 admission outcomes at the two rival programs (in case the applicant applied there as well).

$$\mathbb{1}\left\{adm^{q2}_{ijt}\,|\,y^{q2}_{ijt}=1\right\} = \tilde{\beta}^{q2}_{j0} + \tilde{\beta}^{q2}_{j1}GPA_{it} + \sum_{l}\tilde{\beta}^{q2}_{jl}\mathbb{1}\left\{loc_i=l\right\} + \tilde{\beta}^{q2}_{jn1}\mathbb{1}\left\{NM \succ j\right\} \tag{18}$$
$$+ \sum_{j'\in ODE,AAR,CPH}\mathbb{1}\left\{j'\neq j\right\}\left(\tilde{\beta}^{q2}_{jbj'}\mathbb{1}\left\{y^{q2}_{i,j',t}\right\} + \tilde{\beta}^{q2}_{jsj'}\mathbb{1}\left\{sr^{q2}_{i,j',t}\right\}\right)$$
$$+ \tilde{\beta}^{q2}_{jp1j'}\mathbb{1}\left\{r(j)\right\} + \tilde{\beta}^{q2}_{jp2j'}\mathbb{1}\left\{r(j)\right\} + v^{q2}_{ijt}$$

Fifth, we use linear probability models to match the probability of being ranked by program j in the top 50% of quota 2 applicants above the bar, denoted sr_{ijt}.

$$\begin{aligned}\mathbb{1}\left\{sr_{ijt}\,|\,y^{q2}_{ijt}=1\right\} = {} & \tilde{\beta}^{sr}_{j0} + \tilde{\beta}^{sr}_{j1}GPA_{it} \\ & + \sum_{l}\tilde{\beta}^{sr}_{jl}\mathbb{1}\left\{loc_i=l\right\} + \tilde{\beta}^{sr}_{jn1}\mathbb{1}\left\{NM \succ j\right\} \\ & + \sum_{j'\in ODE,AAR,CPH}\mathbb{1}\left\{j'\neq j\right\}\left(\tilde{\beta}^{sr}_{jbj'}\mathbb{1}\left\{y^{q2}_{i,j',t}\right\} + \tilde{\beta}^{q2}_{jsj'}\mathbb{1}\left\{sr_{i,j',t}\right\}\right) \\ & + \tilde{\beta}^{sr}_{jp1j'}\mathbb{1}\left\{r(j)\right\} + \tilde{\beta}^{sr}_{jp2j'}\mathbb{1}\left\{r(j)\right\} + v^{sr}_{ijt}\end{aligned} \tag{19}$$

Sixth, we target linear probability models of persistence conditional on being matched to program j.

$$\begin{aligned}\mathbb{1}\left\{persist_{ijt}\,|\,match_{ijt}=1\right\} = {} & \tilde{\beta}^{pr}_{j0} + \tilde{\beta}^{pr}_{j1}GPA_{it} + \sum_{l}\tilde{\beta}^{pr}_{jl}\mathbb{1}\left\{loc_i=l\right\} \\ & + \tilde{\beta}^{pr}_{jn1}\mathbb{1}\left\{NM \succ j\right\} + \tilde{\beta}^{pr}_{r1}\mathbb{1}\left\{r(j)\right\} + \tilde{\beta}^{pr}_{q2}\mathbb{1}\left\{y^{q2}_{ijt}\right\} \\ & + \sum_{j'\in ODE,AAR,CPH}\left(\tilde{\beta}^{pr}_{jcj'}\mathbb{1}\left\{y^{q2}_{i,j',t}\right\} + \tilde{\beta}^{pr}_{jsj'}\mathbb{1}\left\{sr_{i,j',t}\right\}\right) + v^{pr}_{ijt}\end{aligned} \tag{20}$$

We discuss the construction of the model analogues of these specifications in the following section.

C.1.2 Estimation Step 2: Non-graduation preferences

With parameters and cutoff functions from step (1) in hand, we estimate a linear approximation to programs' non-graduation preferences. To do so, we first construct persistence propensities for the marginal quota 2 matched students at each program in each observable cell x, denoted y_{jxt}:

$$y_{jxt} \equiv Pr(persist_{ij} | i \in D_{j2}(x), s_{ij} = \underline{s}_{jt}).$$

We then estimate the following WLS regressions of y on $(-x)$ and year indicators, separately by program and pre/post-reform period $\tau(t) \in \{0, 1\}$, with weights proportional to the measure of students in $D_{j2}(x) \cup \{i : s_{ij} = \underline{s}_{jt}\}$:

$$y_{jxt} = \underline{\pi}_{jt} - x'\pi_{xj\tau(t)} + \nu_{jxt}. \tag{21}$$

Year-specific intercepts $\underline{\pi}_{jt}$ allow the quality of the marginal student to change as a function of demand and capacity. Coefficients $\pi_{xj\tau(t)}$ reveal program j's taste for characteristics x. For instance, a positive weight on $1(\text{ODE Local})$ indicates that the program favors Odense locals in quota 2 rankings, beyond what maximizes persistence. If a marginal Odense-local student in year t persists at j with probability p on average, and an otherwise-identical student from elsewhere in Denmark persists with probability p', for some $p' > p \in \{0, 1\}$, then we have $\pi_{1(\text{ODE Local}),j,\tau(t)} = p' - p$ and the program would be said to favor Odense locals by the equivalent of $100(p' - p)$ percentage points.

C.2 Parameter Estimates

This subsection presents estimates of the structural parameters.

Persistence Table 15 presents the estimated persistence parameters α by program and period. As stated in the main text, we hold these parameters fixed over time, except for the constant term. We do allow for time-varying intercepts. The first three columns present pre-reform parameter estimates and the remaining columns present post-reform estimates. Within each period, we first present estimates for Odense, followed by Aarhus and then Copenhagen. At Odense and Aarhus, we find that, conditional on GPA, locals have the highest persistence followed by students from the rival region. Foreigners have by far the lowest persistence rate in all programs.

Applications Table 16 presents the estimated preference parameters γ by program and period, maintaining the column structure from Table 15. Here, we allow all parameters to vary between the pre- and the post-reform period. For Odense and Aarhus, we estimate a sizeable home bias in preferences as indicated by the positive coefficient for locals. Higher GPA students tend to favor Copenhagen over Aarhus and then Odense as suggested by different

Table 15: Persistence Parameters by Program and Period: α

	Pre			Post		
	Ode	Aar	Cop	Ode	Aar	Cop
Constant	-0.56	-1.38	-1.44	-0.56	-1.38	-1.44
GPA	0.03	0.13	0.16	0.03	0.13	0.16
Ode Local	0.50	0.04	-0.13	0.50	0.04	-0.13
Aar Local	0.00	0.39	-0.29	0.00	0.39	-0.29
Foreign	-0.46	-0.72	-0.77	-0.46	-0.72	-0.77

Note: This table presents the estimated persistence parameters α by program and period. The first three columns present pre-reform parameter estimates and the remaining columns present post-reform estimates. Within each period, we first present estimates for Odense, followed by Aarhus and then Copenhagen.

coefficients across columns. Conditional on GPA, foreigners tend to prefer Copenhagen over Odense and Aarhus in the pre-period but their preferences tend to shift towards Odense post-reform. Aarhus also increases in popularity among foreign students. Considering students with a GPA of 10 or higher, the effect of the increased GPA coefficient offsets the drop in the constant term, which suggests that the increase in the foreign coefficient denotes a net increase in popularity of Aarhus among foreigners (relative to the outside good).

Table 16: Application Parameters by Program and Period γ

	Pre			Post		
	Ode	Aar	Cop	Ode	Aar	Cop
Constant	-0.48	-3.65	-6.43	-0.05	-4.19	-6.43
GPA	-0.10	0.27	0.66	-0.17	0.32	0.66
Ode Local	0.91	0.23	-0.51	1.54	0.09	-0.30
Aar Local	-0.06	1.06	-1.93	-0.30	1.03	-1.35
Foreign	0.25	-0.06	0.50	1.36	0.64	1.15

Note: This table presents the estimated preference parameters γ by program and period. The first three columns present pre-reform parameter estimates and the remaining columns present post-reform estimates. Within each period, we first present estimates for Odense, followed by Aarhus and then Copenhagen.

Table 17 presents the estimated mean and variance of the quota 2 application cost (Normal) distribution by program. Means are allowed to vary between the pre- and the post-reform period. Consistent with the main text, we find that application costs increase at Odense between the pre- and the post-reform period, possibly due to the introduction of the additional admission criteria. In contrast, mean application costs remain largely constant at Copenhagen and even fall at Aarhus.

Table 17: Quota 2 Application Costs

	Ode	Aar	Cop
mean (pre)	0.35	0.66	-0.06
mean (post)	0.55	0.20	-0.02
sd	0.22	0.77	0.05

Note: This table presents the estimated mean and variance of the application cost distribution (Normal) by program. The first row presents the post-reform mean and the second row the pre-reform mean. The third row presents the standard deviation. Column 1 presents estimates for Odense, column 2 presents results for Aarhus, and column 3 presents results for Copenhagen.

Admissions Table 18 presents the estimated admission parameters β by program and period, maintaining the column structure from Table 15. Specifically, we present the estimated effects of the variables, denoted in the first column (x), on the signal cutoff ($\underline{s}_{jt}(x)$), denoted by β^x_{jt} in the main text discussion. Lower parameters indicate a lower cutoff and hence higher admission chances. At Odense and Aarhus, local students have lower admissions cutoffs consistent with their higher average persistence rate discussed in Table 15. Likewise, foreigners tend to have lower admission chances, conditional on GPA, consistent with their lower persistence rates. The constant terms are allowed to vary by year and we delegate further discussion to the supplementary materials, Table 25.

Table 18: Admission Parameters by Program and Period β

	Pre			Post		
	Ode	Aar	Cop	Ode	Aar	Cop
GPA	-0.12	-0.51	0.09	0.05	-0.10	0.14
Ode Local	-0.21	0.32	0.56	-0.05	0.09	0.87
Aar Local	-0.12	0.26	0.27	-0.38	0.22	0.56
Foreign	1.33	0.38	0.85	0.60	-0.04	0.91

Note: This table presents the estimated admission parameters β by program and period. The first three columns present pre-reform parameter estimates and the remaining columns present post-reform estimates. Within each period, we first present estimates for Odense, followed by Aarhus and then Copenhagen. We exclude the constant term from this table as we allow for year-specific intercepts presented in Table 25.

Finally, we present the estimated non-graduation preference parameters in Table 19. The columns follow again the structure of Table 15. The constant terms are normalized to zero. Most parameter estimates are relatively small except for the positive foreign coefficients, which indicate positive non-persistence preferences of programs over foreign students. Put differently, if admission were purely made based on persistence potential, foreigners would have even smaller admission chances due to a lower persistence rate, see again Table 15.

Table 19: Nongraduation Preferences Parameters by Program and Period π

	Pre			Post		
	Ode	Aar	Cop	Ode	Aar	Cop
Constant	0.00	0.00	0.00	0.00	0.00	0.00
GPA	0.02	-0.06	-0.06	-0.02	0.01	-0.01
Ode Local	-0.00	-0.07	0.04	-0.01	-0.02	-0.03
Aar Local	-0.14	0.02	0.00	-0.05	-0.01	-0.01
Foreign	-0.07	0.36	0.47	0.22	0.45	0.39

Note: This table presents the estimated nongraduation preference parameters π by program and period. The first three columns present pre-reform parameter estimates and the remaining columns present post-reform estimates. Within each period, we first present estimates for Odense, followed by Aarhus and then Copenhagen. The constant terms are normalized to zero.

Lastly, we combine admission and non-graduation preferences in Table 20 to describe the average admission bias by region of residence before and after the reform.

Table 20: Net Admission Preferences Parameters by Program and Period π

Location	Ode Pre	Aar Pre	Cop Pre	Ode Post	Aar Post	Cop Post
Ode Local	-1.30	-0.83	1.44	0.41	-0.83	2.12
Aar Local	-1.35	-0.80	1.12	0.03	-0.69	1.82
Foreign	0.18	-0.34	2.16	1.29	-0.49	2.58

Note: This table adds the estimated non-graduation preference parameters π by program and period, see Table 19 to the persistence based admission cutoffs, see Table 18 for students with a GPA of 8. The first three columns present pre-reform parameter estimates and the remaining columns present post-reform estimates. Within each period, we first present estimates for Odense, followed by Aarhus and then Copenhagen. The rows show the cutoffs ignoring the constant terms.

Information Structure: To facilitate the interpretation of the relationship between latent persistence shocks, preference shocks and signals, we present regression coefficients governing their statistical relationship. Specifically, we consider

$$\omega_j | e, s \sim \Phi((\epsilon, s)' * b, \Sigma_w).$$

and present the estimated coefficients, c, by program in Table 22 for the post-reform period. We report the full covariance matrix of the preference shocks ϵ, signals s, and unobserved persistence shocks ω as supplementary material in Tables 26 and 27.

In Table 22, we find that preferences for a program are positively correlated with signals at Odense and Copenhagen. At Aarhus, we find a negative correlation, which may partially reconcile the relatively large coefficients on signals and own preferences at Aarhus in Table 21. Specifically, larger preference shocks have a relatively large positive effect on persistence at Aarhus but also lower the own signal, which will in turn mute the net effect on persistence. We find a negative relationship between preferences for the outside good ϵ_0 and the signal at Aarhus and Copenhagen in Table 22. We find a small positive relationship at Odense, which may again mute the effect of preference shocks for the outside good on persistence.

Turning to the programs' signals, we find that the own signal is positively correlated with unobserved persistence in each program.

Table 21: Results Omega

var	ω **Ode Post**	ω **Aar Post**	ω **Cop Post**
ε Ode	0.288	-0.005	0.038
ε Aar	0.097	0.581	0.094
ε Cop	0.181	0.237	0.445
$\varepsilon 0$	-0.325	-0.501	-0.319
s Ode	0.075	-0.011	0.066
s Aar	0.263	0.924	0.243
s Cop	-0.359	-0.668	-0.333

Note:This table presents the estimated coefficients b, as defined in $\omega_j|e, s \sim \Phi((\epsilon, s)' * b, \Sigma_w)$ by program for the post-reform period.

To further explore the relationship between signals and preference shocks, we also present regression coefficients governing their statistical relationship. Specifically, we consider

$$s_j|\epsilon \sim \Phi(\epsilon' c, \Sigma_s)$$

and present the estimated coefficients, c, by program in Table 22 for the post-reform period. We find that own preferences are positively correlated with signals at Odense and Copenhagen. At Aarhus, we find a negative correlation, which may partially reconcile the relatively large coefficients on signals and own preferences at Aarhus in Table 21. Specifically, larger preference shocks have a relatively large positive effect on persistence at Aarhus but also lower the own signal, which will in turn mute the net effect on persistence. We find a negative relationship between preferences for the outside good ϵ_0 and the signal at Aarhus and Copenhagen in Table 22. We find a small positive relationship at Odense, which may again mute the effect of preference shocks for the outside good on persistence.

Table 22: Progam Signals

var	s **Ode Post**	s **Aar Post**	s **Cop Post**
ε Ode	0.297	-0.128	-0.082
ε Aar	-0.025	-0.279	-0.077
ε Cop	-0.023	-0.108	0.297
$\varepsilon 0$	0.278	-0.081	-0.687

Note: This table presents the estimated coefficients, c, as defined in $s_j|\epsilon \sim \Phi(\epsilon' c, \Sigma_s)$ by program for the post-reform period.

D Appendix: Counterfactuals

In this section, we provide details on the counterfactual analysis.

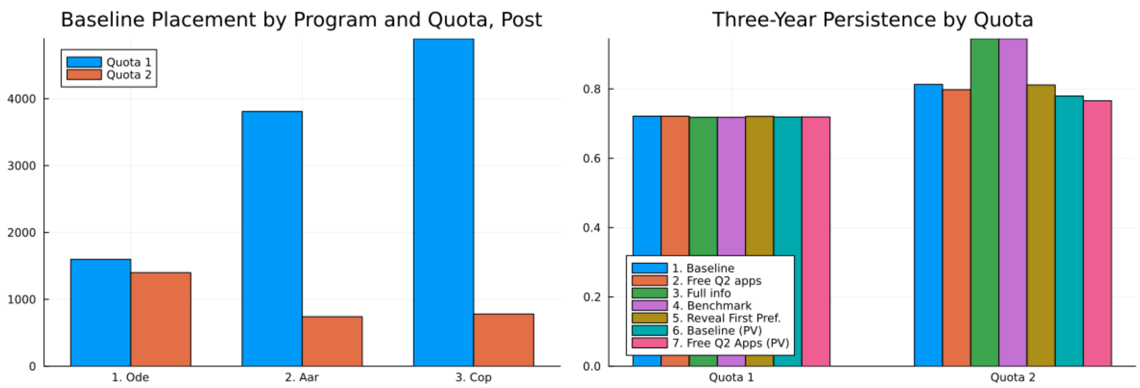
Quota 1 and Quota 2 Students As noted in the main text, we focus our analysis on quota 2 students. The left graph of Figure 12 presents annual placements by quota and program to give context. The right graph presents select counterfactual persistence rates, detailed further below, by quota. There are no notable changes for students admitted via quota 1, we therefore focus on the counterfactual discussion in the main text, and the following discussion here, on quota 2 students.

Details on Counterfactual Analysis We proceed in three steps: First, we assess the relative importance of applicants' self-selection and programs' screening efforts by making applications free. Second, we quantify the overall scope for improvements in student outcomes under full information. Third, we consider how an alternative information structure where programs learn which applicants applied as their first priority may help mitigate the impact of information asymmetries.

First, we find that making Q2 application free hurts programs with higher baseline application costs, but can benefit their rival programs with initially low application costs. This illustrates the value of advantageous self-selection of students if application costs are high. If programs only rely on their own screening efforts with a large and unselected applicant pool, the average quality of admitted students declines. Aarhus is the exception, improving its persistence rate by benefiting from high-quality students who could no longer signal their type to high-cost programs and were rejected there.

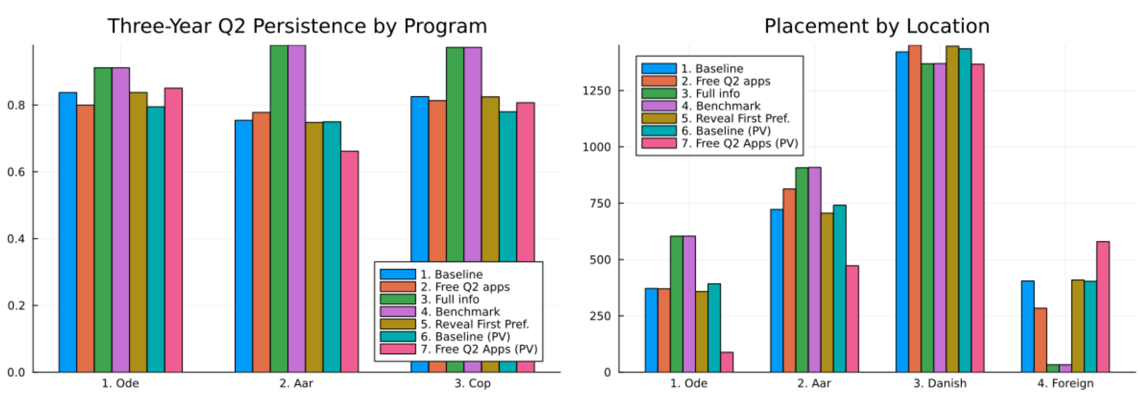
Second, we quantify the scope for improvements in the outcome of interest (3-year

Figure 12: Placements and Persistence by Quota and Program



Note: This figure summarizes the number of placements and the average persistence rate by quota in the post-reform period. The left figure presents the baseline number of placements by quota and program in the estimated common values model. The right graph presents the average persistence rate by quota across a number of counterfactual exercises. The left bars present persistence rates for quota 1 admissions and the right bars present analogous evidence for quota 2 admissions, averaged over medical school programs. The first bar (displayed in blue) denotes the baseline persistence rate, and the second bar (orange) presents the persistence rate after setting quota 2 application costs to zero. The third bar (green) denotes the persistence rate after removing quota 2 application costs and informing programs about rival signals as well as applicants' preference shocks. The fourth bar (purple) further removes non-graduation preferences in the programs' admission preferences. Finally, the last bar (displayed in beige) denotes average persistence rates when programs can observe and use the student's first quota 1 preference in their quota 2 admission decisions.

Figure 13: Counterfactual Placement and Persistence of Quota 2 Students



Note: The left figure presents persistence by program across a number of counterfactuals. The right graph presents enrollment in any medical school program by region of residence across the same counterfactuals. Going linearly through the counterfactuals, the first bar (displayed in blue) denotes the baseline persistence rate, and the second bar (orange) presents the persistence rate after setting quota 2 application costs to zero. The third bar (green) denotes the persistence rate after removing quota 2 application costs and informing programs about rival signals as well as applicants' preference shocks. The fourth bar (purple) further removes non-graduation preferences in the programs' admission preferences. Finally, the last bar (displayed in beige) denotes average persistence rates when programs can observe and use the student's first quota 1 preference in their quota 2 admission decisions.

persistence rates) through changes in the information structure. To this end, we consider the case where applications are free and all signals and utilities are commonly observed. This means that programs can make admission decisions for the universe of interested candidates utilizing both sources of private information that they lack in the baseline: applicants' information about their preferences and rivals' signals about applicant performance. Thus, the difference between the baseline and this "full info" scenario quantifies the maximum potential for better information to improve overall student outcomes. Our results suggest that these potential gains are large, as indicated by the substantial increases in average persistence across programs. This is an important finding that emphasizes the role of asymmetric information in this market.

These gains are realized through a substantial change in the regional composition of students. One crucial student subpopulation in our setting is foreign students who have relatively low average persistence rates. Yet, under substantial uncertainty about each applicant's potential, programs admit many foreigners in quota 2 at baseline. In contrast, the full information scenario substantially reduces the number of admitted foreign applicants because the additional information from applicants and rivals helps each program eliminate many false positives among foreign applicants.

Finally, we turn to possible changes in the information structure and ask to what extent they can move the allocation in this market from the baseline closer to the full information benchmark. In general, possible policies could include information sharing among programs or opportunities for applicants to signal their preferences. Here, we explore the effects of one such policy, related in spirit to the popular "Early Decision" round at U.S. colleges. Specifically, we implement this policy by informing programs whether the applicant listed them first. In the DA mechanism in this market, listing a program first is a credible signal of private information and foregoes the option to get admitted to lower-priority programs in the case of admission at the first choice. As with "Early Decision", this information revelation can lead to strategic application behavior depending on how programs factor in the first-choice signal into their admission policy.

Figure 13 shows that the first-preference counterfactual only generates small changes in persistence. Table 23 explores the mechanism underlying this result: First, conditional on applicant preferences for medical and non-medical programs, significantly fewer candidates list non-medical programs first in the first-preference scenario compared to the baseline (see column 1). Column 2 shows that applicants who list non-medical programs first have almost 5 p.p. lower expected persistence rates in medical programs. This negative selection decreases only slightly in the first-preference scenario. Taken together, this suggests that students with stronger preferences for non-medical programs but low persistence rates take advantage of the first-preference signal to boost overall admission chances, in turn watering

Table 23: Details on First-Preference Scenario

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}\{$non-med first$\}$	Pr(persist)	$\mathbb{1}\{$non-local first$\}$	Pr(persist)	$\mathbb{1}\{$foreign first$\}$	Pr(persist)
first-pref	-0.0268***	-0.0032***	0.0033**	-0.0009	0.0031***	0.0016
	(0.002)	(0.001)	(0.001)	(0.004)	(0.001)	(0.002)
non-med first		-0.0472***				
		(0.001)				
non-med first $\times$ first-pref		0.0033***				
		(0.001)				
non-local first				0.0931***		
				(0.006)		
non-local first $\times$ first-pref				0.0006		
				(0.004)		
foreign						-0.0606***
						(0.008)
foreign $\times$ first-pref						-0.0092**
						(0.004)
Observations	186,280	558,840	43,124	43,124	43,124	43,124
Sample	Applicants	Applications	Matches	Matches	Matches	Matches
Medical Pref Controls:	Yes	Yes	No	No	No	No
Non-Medical Pref Controls:	Yes	No	No	No	No	No
GPA FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	No	No	No	No

Note: This table presents linear regression models for simulated data from the baseline model and from the first-preference scenario. All regressions control for GPA fixed effects. The "first-pref" variable is an indicator for the first-preference scenario. The "non-med first" is an indicator variable that takes value one if an applicant lists a non-medical program first, and"non-local first" is an indicator for an applicant from a non-local region in Denmark listing a particular medical program first.

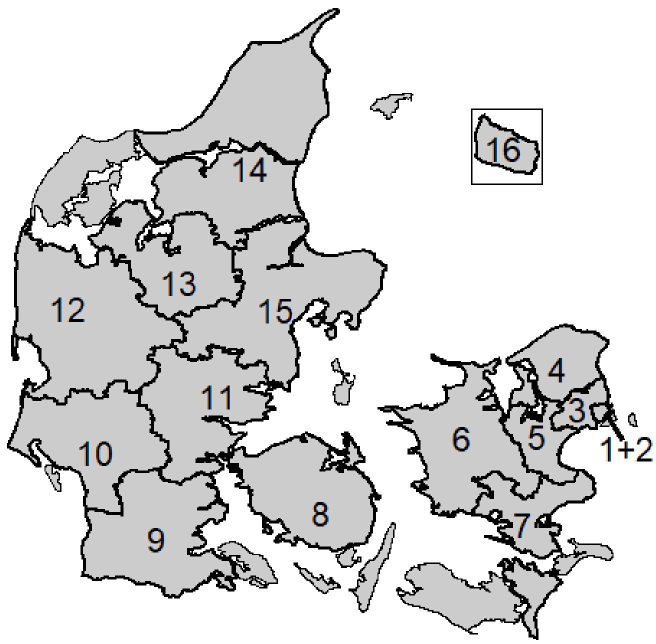
down the value of the signal. Second, programs now admit only slightly more students from rival regions who use the first-priority bonus to signal their interest (column 3), even though the persistence rates among such students from rival regions are high and unchanged in the first-preference scenario (column 4). Third, the probability of admitting foreigners who list the medical program first increases by the same amount as for non-local Danes (column 5), but foreigners have significantly lower persistence rates, and this disadvantage is further exacerbated in the first-preference scenario (column 6). Overall, many marginal students take advantage of this policy, and thus the signal provides limited additional information to programs.

Supplementary Materials (Not for Publication)

E Supplement: Data and Institutions

E.1 Danish Geography

Figure 14: Counties of Denmark



	Description	Our Location Code
1+2	Copenhagen and Frederiksberg Municipalities	0
3	Copenhagen Greater County	0
4	Frederiksborg County	0
5	Roskilde County	0
6	West Zealand County	1
7	Storstrom County	1
8	Funen County (Location of Odense)	1
9	South Jutland County	1
10	Ribe County	0
11	Vejle County	2
12	Ringkjobing County	0
13	Viborg County	2
14	North Jutland County	2
15	Aarhus County	2
16	Bornholm	0

E.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, so we use 1994 as the 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 increases 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 courses.
- 2007: A new grade scale is introduced collapsing the ten previous individual grades into seven broader categories. GPAs obtained from graduation before 2007 are converted via a fixed table (see first page: `shorturl.at/vHOR6` last accessed Jan 25, 2020).
- 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 formalized 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 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. This grade bonus was canceled again in 2020. The course requirements for Bachelor's programs in general are loosened, and medicine is not affected. The conditions for earning extra "turbo" credits during the summer are 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 to 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 re-exams. The SU grant is removed if a student falls too far behind. The student earns a bonus for completing on time.
- 2015: Last cohort of application data on project 4937. Aalborg University (AAU) increased its medicine program from 50 seats to 110. Aarhus University (AU) pilots test Multiple-Mini-Interviews as an intensified screening process in medicine.
- 2016: Aarhus University (AU) increased its medicine Q2 share from 10 to 20 pct. and introduced Multiple-Mini-Interviews in addition to a multiple-choice admission test. The MMI's were dropped in 2018.

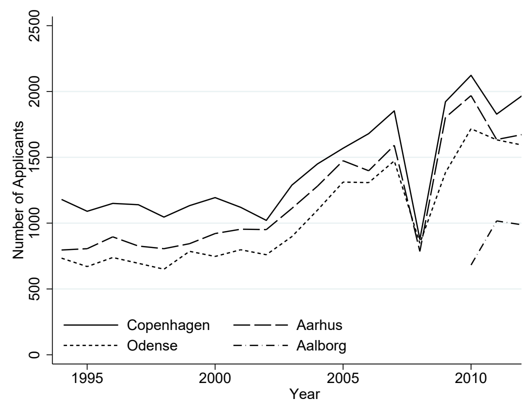
F Supplement: Empirical Results

F.1 Background Information: Applications

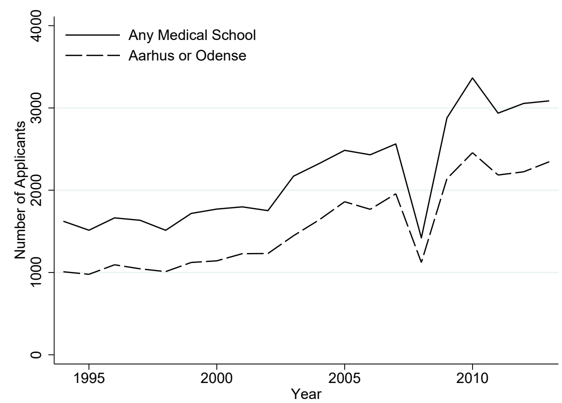
Figures 15a and 15b depicts the size of the applicant pool for Danish medical schools by program and in total. In terms of applications, and likely also reflecting the program sizes illustrated in Figure 16a, Copenhagen is consistently the most popular program followed by Aarhus and Odense. Both across programs and in terms of unique medicine applicants, applications per year are gradually increasing over the sample period. Applications in 2008 exhibit a notable decline coinciding with heightened prerequisites for university admissions in general and Medicine programs in particular, see Appendix E.2.

Applicant GPA has also been increasing over time, as illustrated in Figure 15c. The GPA scale changed from a 13-point to a 7-point scale in 2007. We use the official conversion table, see Appendix E.2, to harmonize high school GPAs and admissions thresholds in all years to a unifying scale. However, as evident from the figure, the implemention of the simplified grading scale changed the distribution of GPAs in the right tail in particular. Copenhagen consistently attracts the most competitive applicants, followed by Aarhus and Odense, see e.g. Figure 15d for applicant cohorts in 2005 and 2006.

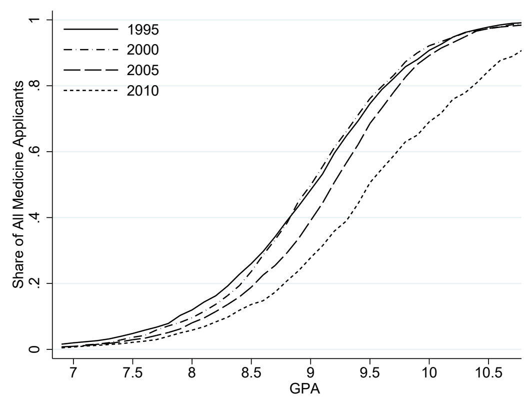
Figure 15: Applications and Applicants to Medical Schools



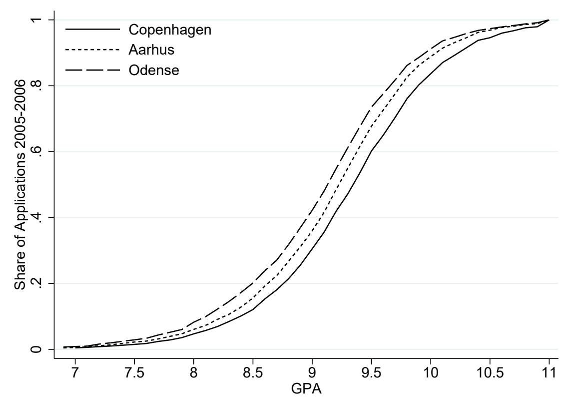
(a) Number of Applications by Program



(b) Number of Unique Applicants



(c) Applicants' GPA Distribution



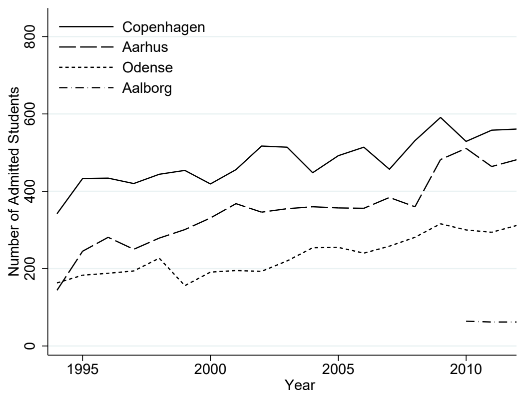
(d) Applicants' GPA by Program 2005/06

Note: Figure 15a shows the annual number of applicants who list each medical school among their up to 8 priorities, while Figure 15b reports the total number of unique applicants who apply. Figure 15c presents the high school GPA distribution of applicants in select years across programs. Each cohort includes applicants who indicate at least one medical school programs in their submitted preference ranking. GPA is harmonized to the 7-point scale in all years. Figure 15d shows applicants' GPA by medical program, pooling applicant cohorts 2005 and 2006.

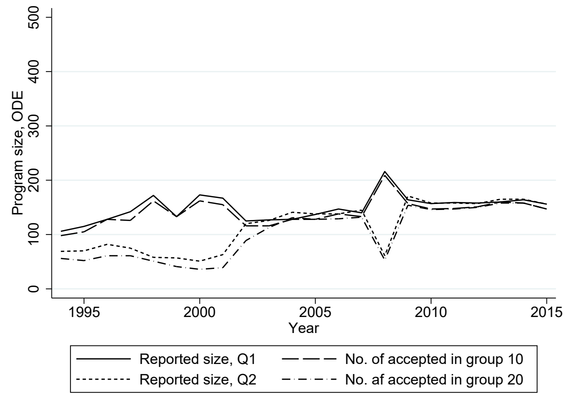
F.2 Background Information: Admissions

Capacity Figure 16a describes the total number of admissions by program and year. Overall, admissions are quite stable over time, with a modest expansion across all existing

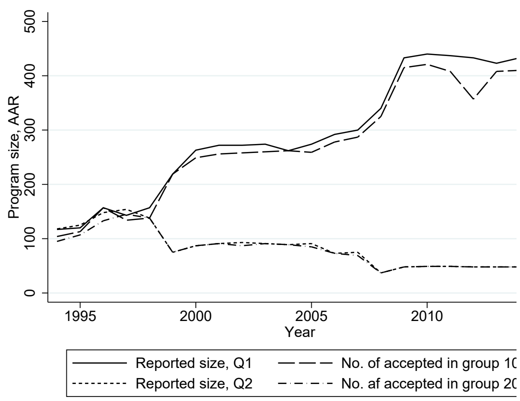
Figure 16: Admissions to Medical School Programs 1994-2013



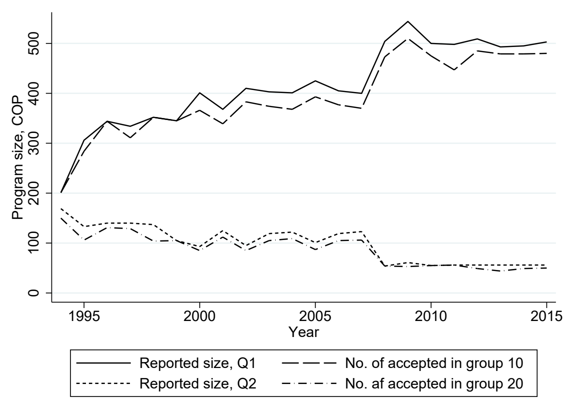
(a) Admissions to Medicine Programs



(b) Program Size, Odense



(c) Program Size, Aarhus



(d) Program Size, Copenhagen

Notes: Data come from the Danish Central Admissions Secretariat (CAS). Copenhagen and Odense increased their capacity by 50 seats in 2009, whereas Aarhus increased their capacity by 100 seats in 2009, see Figure 16a. Figures 16b - 16d show the annual number of seats in Quota 1 and 2 in Odense, Aarhus, Copenhagen respectively. Our sample includes all applicants accepted through groups 10 and 20, which represent the vast majority of admitted students in each quota.

programs in 2009: Copenhagen and Odense increased their capacity by 50 seats, while Aarhus expanded by 100 seats, see Section E.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 1,800 in the late 1990s to 3,300 after 2010, see Figure 15. Our analyses focus on admissions through application groups 10 (subset of quota 1) and 20 (subset of quota 2), illustrated in Figures 16b - 16d, which collectively constitute over 90% of all medical school admissions. This criterion is necessary as applicants are ranked within groups only, and the relative ranking of applicants is therefore not comparable across groups. Groups 10 and 20 cover all regular admissions and exclude for example standby admissions and applicants from non-EU countries, e.g. Norway, who are ranked separately in their own group with a small number of program seats.

F.3 Evidence on Rejection Chains

For rejection chains to be attractive from a particular program P's perspective, several conditions have to be satisfied at the same time. Suppose 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 a lower priority and will subsequently be admitted at one of them.

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 24, 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 have less than 20% and 10% chance of subsequently being admitted to another medical program, respectively.

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 24 shows that 42% and 71% of marginal Q1 students from rival programs would be admitted at Odense and Aarhus, respectively. The shares among marginal Q2 students at rivals is considerably lower at 23% and 13% for Odense and Aarhus, respectively. Copenhagen is much more selective and would only admit 4-5% of marginal students at rival programs.

We benchmark the overall attractiveness of rejection chains in Panel E of Table 24. Take Odense as an example. If all rejected candidates A trigger a rejection chain that allows Odense to assess a new candidate, who would have otherwise been admitted at the rival program, then the probability of admitting a student preferred to A is $0.02 * 0.42 + 0.079 * 0.229 = 2.65\%$. But since admission at medical schools is very competitive, those who do not list Odense as their next priority will likely be admitted to a different program. In that sense, the 2.65% success rate is an upper bound. The analogous bounds for Aarhus and Copenhagen are 4.25% and 2.1%, respectively.

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

In sum, we find that the potential of successful rejection chains may be limited in practice.

Table 24: Empirical Assessment of the Potential for Rejection Chains

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

G Supplement: Model

G.1 Quota 2 Applications

In this section, to illustrate students' optimal application problem, we consider a setting with two programs, and explicitly construct the expeccted value of each quota-2 application portfolio. 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

$$u_j \times \Big(Pr(j|\{j\}) - Pr(j|\emptyset)\Big) > c_{\{j\}}. \tag{22}$$

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

$$v_a = Pr(1|a) \times u_1 + Pr(2|a) \times u_2 - c_{\{a\}} , \tag{23}$$

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

$$v_{a'} - v_a \leq 0 \text{ for all } a' \neq a.$$

H Supplement: Estimation

H.1 Details on Computation

We construct a smooth GMM objective function, permitting the use of gradient-based optimization routines. To do so, we construct the likelihood of each history at each trial parameter vector. We then estimate our auxiliary LPM specifications (model-predicted means) in a dataset consisting of all histories, via weighted least squares (weighted averages) as follows.

Smooth Indirect-Inference Estimator: Ordering all possible histories $h = 1, \ldots, H$ arbitrarily, let let $L(\theta)$ be a vector of length H whose hth entry is the measure of students with history h under parameters θ. Consider auxiliary specification $r = 1, \ldots, R$ where R is the number of auxiliary specifications that were estimated, and let its coefficients be denoted $\tilde{\beta}^r$.

Let $\tilde{X}^{\text{model},r}$ be a (H, K) matrix of regressors for auxiliary linear-probability model r, whose hth row consists of the value of the regressors that correspond to history h. Let $\tilde{Y}^{\text{model},r}$ be a (H)-vector containing the values of the dependent variable corresponding to each history. We have

$$\tilde{\beta}^{\text{model},r}(\theta) = ((\tilde{X}^{\text{model},r})' L(\theta) \tilde{X}^{\text{model},r})^{-1} (\tilde{X}^{\text{model},r})' L(\theta) \tilde{Y}^{\text{model},r}.$$

Our moments are then given by

$$g^{\text{LPM,r}}(\theta) = ||\tilde{\beta}^{\text{model},r}(\theta) - \tilde{\beta}^r||.$$

In order to compute our GMM estimator, we compute the measure of each history. To do so, for each cell of observables, we compute the likelihood of each history consistent with the cell, then multiply by the mass of students in the cell. Computing the matrix of regressors $\tilde{X}^{\text{model},r}$ and outcome vector $\tilde{Y}^{\text{model},r}$ can be done once, offline.

Other details: We integrate over ε using Monte Carlo methods. For a cell with N people we take $M = 2N$ iid normally-distributed utility-vector draws. To compute the expected value of each portfolio in order to compute quota 2 application probabilities, we integrate over application cost vectors with 128 independent normal cost-vector draws per cell.

For each utility vector, there are 27 possible sub-histories corresponding to vectors of offer and top-50 offer outcomes. Say offer$_{ij}$ = 2 if the student receives a "top 50%" offer (i.e.

has $s_{ij} > \overline{s}_{j,t}$ where t is the year in which i applies), 1 if the student is above the bar but not in the "top 50%" (i.e. $\overline{s}_{j,t} > s_{ij} > \underline{s}_{j,t}$), and 0 if the student's signal is below the admission cutoff. Any outcome in $\{0, 1, 2\}^3$ is possible. We use the Genz algorithm (Genz, 1992) to integrate over realizations of s in order to compute the measure of these sub-histories, and the conditional expectation of ω_j conditional on these sets.

H.2 Details on Parameter Estimates

Admissions In this section, we complement Table 18, which presents the estimated admission parameters β by program and period.

The constant terms are allowed to vary by year and are presented in Table 25. These parameters correspond to the cutoffs in quota 2 admissions, denoted by (β^0_{jt}) in the main text. Columns 2-3 present results for Odense, columns 4-5 present estimates for Aarhus, and columns 6-7 present results for Copenhagen. Within each program, the first column presents the cutoff estimates. To facilitate the interpretation, the second column presents the approximate admission chance in the given year for a given student type, $\bar{x}$. Specifically, we consider a GPA of 9 (below the quota 1 cutoff) from the Odense region and then display the (approximate) probability of being above the cutoff: $1 - \Phi(\beta^0_{jt} + \bar{x} \times \beta_{jt})$. The quota 2 admission chances tend to fall over time in each program. This is in part because of decreasing quota 2 admission shares at Aarhus and Copenhagen but also because of an increase in the number of applicants, see Figure 15.

Information Structure Table 26 presents the estimated covariance matrix of the preference shocks ϵ, signals s, and unobserved persistence shocks ω for the pre-reform period. Analogous estimates for the post-reform period are presented in Table 27.

Table 25: Quota 2 Admissions Cutoffs by Program and Year

Year	Ode	Ode Adm. Chance	Aar	Aar Adm. Chance	Cop	Cop Adm. Chance
1994	1.62	0.08	3.86	0.51	-0.29	0.05
1995	-1.95	1.00	2.02	0.79	-0.49	0.07
1996	0.61	0.63	2.60	0.85	-0.35	0.05
1997	0.96	0.29	2.75	0.82	-0.33	0.06
1998	-0.22	0.90	2.20	0.83	-0.38	0.05
1999	1.11	0.23	2.96	0.71	-0.25	0.04
2000	1.11	0.34	2.83	0.75	-0.10	0.03
2001	0.95	0.35	2.63	0.81	-0.31	0.05
2002	-0.02	0.16	0.18	0.47	-0.37	0.01
2003	0.17	0.12	0.42	0.54	-0.16	0.00
2004	0.02	0.15	0.48	0.53	-0.23	0.01
2005	0.18	0.12	0.62	0.46	-0.04	0.00
2006	0.36	0.09	0.76	0.40	-0.07	0.01
2007	0.13	0.14	0.75	0.43	-0.06	0.00
2009	0.05	0.16	0.97	0.31	0.43	0.00
2010	0.26	0.12	1.04	0.25	0.51	0.00
2011	0.11	0.12	0.97	0.29	0.47	0.00
2012	0.15	0.12	0.99	0.30	0.53	0.00
2013	0.26	0.12	1.06	0.27	0.65	0.00

Note: This table presents the estimated cutoffs in quota 2 admissions, denoted by (β^0_{jt}) in the main text. The coefficients are allowed to vary by year, as indicated in the first column. Columns 2-3 present results for Odense, columns 4-5 present estimates for Aarhus, and columns 6-7 present results for Copehagen. Within each program, the first columns present estimates for being above the bar and the second columns present the approximate admission chance for a student from Odense with a GPA of 9.

Table 26: Results Omega Pre-Reform

	variable	ε Ode	ε Aar	ε Cop	ε_0	s Ode	s Aar	s Cop	ω Ode	ω Aar	ω Cop
0	ε Ode	1.961338	0.959708	2.026201	-0.038187	0.187406	-0.788925	-0.311970	0.546958	0.263071	0.326716
1	ε Aar	0.959708	1.958081	2.022766	-0.038122	-0.372756	-1.330115	-0.311441	0.199668	0.668835	0.326162
2	ε Cop	2.026201	2.022766	5.270599	-0.080486	-0.786987	-1.662808	-0.167518	0.421552	0.554473	0.753078
3	ε_0	-0.038187	-0.038122	-0.080486	1.001517	-0.479592	-0.061893	-0.177346	-0.424321	-0.309154	-0.124411
4	s Ode	0.187406	-0.372756	-0.786987	-0.479592	1.000000	0.402423	-0.054243	0.589712	0.251423	0.183929
5	s Aar	-0.788925	-1.330115	-1.662808	-0.061893	0.402423	1.000000	0.184781	-0.107807	-0.384760	-0.229129
6	s Cop	-0.311970	-0.311441	-0.167518	-0.177346	-0.054243	0.184781	1.000000	0.102030	0.086964	0.090836
7	ω Ode	0.546958	0.199668	0.421552	-0.424321	0.589712	-0.107807	0.102030	1.000000		
8	ω Aar	0.263071	0.668835	0.554473	-0.309154	0.251423	-0.384760	0.086964		1.000000	
9	ω Cop	0.326716	0.326162	0.753078	-0.124411	0.183929	-0.229129	0.090836			1.000000

Note: This table presents the estimated covariance matrix of the preference shocks ϵ, signals s, and unobserved persistence shocks ω for the pre-reform period.

Table 27: Results Omega Post-Reform

	variable	ε Ode	ε Aar	ε Cop	ε_0	s Ode	s Aar	s Cop	ω Ode	ω Aar	ω Cop
0	ε Ode	3.009910	1.885876	1.698964	-0.063010	0.790523	-1.088268	0.157826	1.092553	0.394609	0.802755
1	ε Aar	1.885876	2.769496	1.594119	-0.059122	0.437539	-1.180642	0.148086	0.786808	0.812425	0.753216
2	ε Cop	1.698964	1.594119	2.436124	-0.053262	0.394174	-0.919906	0.499627	0.708827	0.333561	0.951008
3	ε_0	-0.063010	-0.059122	-0.053262	1.001975	0.262193	-0.050618	-0.694827	-0.103356	-0.134597	-0.114300
4	s Ode	0.790523	0.437539	0.394174	0.262193	1.000000	-0.149454	-0.019578	0.298675	0.076168	0.199103
5	s Aar	-1.088268	-1.180642	-0.919906	-0.050618	-0.149454	1.000000	0.227488	-0.406965	-0.099129	-0.388288
6	s Cop	0.157826	0.148086	0.499627	-0.694827	-0.019578	0.227488	1.000000	0.075286	0.094730	0.184172
7	ω Ode	1.092553	0.786808	0.708827	-0.103356	0.298675	-0.406965	0.075286	1.000000		
8	ω Aar	0.394609	0.812425	0.333561	-0.134597	0.076168	-0.099129	0.094730		1.000000	
9	ω Cop	0.802755	0.753216	0.951008	-0.114300	0.199103	-0.388288	0.184172			1.000000

Note: This table presents the estimated covariance matrix of the preference shocks ϵ, signals s, and unobserved persistence shocks ω for the post-reform period.

H.3 Supplement: Model Fit

Table 28: Q1 Applications

	Pre			Post		
	Model	Data	SD Data	Model	Data	SD Data
Apply Q1 Aarhus						
constant	-2.605	-2.062	0.088	-2.518	-2.236	0.058
GPA	0.194	0.120	0.010	0.194	0.161	0.006
ode	0.167	0.297	0.025	0.055	0.103	0.021
aar	0.755	0.683	0.019	0.619	0.552	0.014
foreign	-0.040	0.293	0.031	0.387	0.531	0.016
Apply Q1 CPH						
constant	-2.803	-2.803	0.086	-4.122	-2.712	0.058
GPA	0.286	0.284	0.010	0.421	0.259	0.006
ode	-0.222	-0.261	0.023	-0.195	-0.268	0.020
aar	-0.839	-0.703	0.020	-0.866	-0.686	0.015
foreign	0.218	-0.053	0.029	0.738	0.458	0.016
Apply Q1 Odense						
constant	-0.341	-0.627	0.089	-0.030	-0.565	0.058
GPA	-0.074	-0.042	0.010	-0.098	-0.017	0.006
ode	0.646	0.622	0.023	0.889	0.623	0.019
aar	-0.043	0.098	0.021	-0.171	-0.123	0.015
foreign	0.180	0.262	0.032	0.781	0.584	0.016
Apply Q1 NM						
constant	0.700	0.806	0.024	0.923	0.834	0.018
GPA	0.031	0.022	0.003	0.006	0.016	0.002
aar	0.085	-0.002	0.006	-0.001	-0.004	0.005
ode	0.028	-0.021	0.007	0.011	0.031	0.007
foreign	0.018	0.031	0.009	0.142	0.096	0.005
Q1 App Aarhus	0.775	0.817	0.008	0.789	0.829	0.006
Q1 App Aar Ode	1.704	1.781	0.009	1.728	1.741	0.007
Q1 App Ode Aar	1.659	1.828	0.011	1.771	1.810	0.007
Q1 App Odense	0.756	0.800	0.010	0.818	0.852	0.007
Q1 App CPH	0.835	1.000	0.017	0.889	0.741	0.011
Q1 App CPH First	0.062	-0.171	0.017	-0.058	0.132	0.011
Q1 App CPH Second	0.033	-0.060	0.019	-0.019	0.137	0.013

Note: This table presents estimates of probit models, described in equation (14) (first three panels), and linear regression models, described in equation (16) (last panel). The first three columns analyze the pre-reform period 1994-2001 and the second three columns analyze the post-reform period, 2002-2013. The first column in each group denotes the estimates from the simulated, the second column denotes estimates on the data, and the third column presents the standard error on the point estimates in the data. The table is organized into four panels. The first three panels analyze quota applications to Aarhus, Copenhagen, and Odense, respectively. The last panel presents results for quota 1 applications to non-medical programs.

Table 29: Q2 Applications: LPM

	Pre			Post		
	Model	Data	SD Data	Model	Data	SD Data
Apply Q2 Aarhus						
Total Apps	1622.358	1601.000	nan	6601.728	6602.000	nan
constant	0.288	0.322	0.071	0.522	0.617	0.047
GPA	-0.008	-0.022	0.007	-0.013	-0.040	0.005
aar	0.016	0.026	0.013	0.007	-0.011	0.009
ode	0.006	-0.034	0.015	0.014	-0.091	0.013
foreign	0.016	-0.137	0.198	0.045	-0.564	0.101
Pref NM over A	0.008	-0.022	0.014	-0.006	0.079	0.009
Apply Q1 Odense	-0.015	0.018	0.013	-0.007	0.077	0.009
Apply Q2 Odense	-0.051	0.245	0.025	-0.025	0.071	0.015
Prefer Aar to Ode	0.006	0.066	0.015	0.006	0.007	0.010
Q2 App Ode but pref A	0.007	0.044	0.035	0.000	0.149	0.023
Apply Q1 CPH	0.023	-0.153	0.023	-0.001	-0.269	0.015
Apply Q2 CPH	-0.023	0.227	0.021	-0.010	0.557	0.013
Prefer Aar to CPH	0.006	-0.003	0.028	0.006	0.029	0.017
Q2 App CPH but pref A	0.007	0.121	0.032	0.004	0.018	0.020
Apply Q2 CPH						
Total Apps	6105.098	6105.000	nan	11617.460	11617.000	nan
constant	1.006	2.884	0.063	0.781	2.568	0.035
GPA	-0.041	-0.256	0.006	-0.025	-0.233	0.003
aar	-0.008	-0.029	0.015	-0.010	0.025	0.009
ode	-0.009	-0.033	0.013	-0.013	-0.018	0.010
foreign	-0.008	-1.861	0.171	-0.034	-1.896	0.073
Pref NM over C	-0.030	-0.018	0.013	-0.028	-0.081	0.008
Apply Q1 Odense	0.002	0.018	0.013	0.014	0.057	0.007
Apply Q2 Odense	-0.060	0.187	0.030	-0.049	0.174	0.016
Prefer CPH to Ode	0.035	0.067	0.019	0.024	0.001	0.010
Q2 App Ode but pref C	0.043	-0.038	0.039	-0.014	0.050	0.020
Apply Q1 Aarhus	0.039	0.009	0.014	0.012	-0.077	0.008
Apply Q2 Aarhus	-0.019	0.258	0.023	-0.006	0.449	0.013
Prefer CPH to Aar	0.016	-0.020	0.019	0.020	0.062	0.011
Q2 App Aar but pref C	-0.007	-0.019	0.031	-0.004	-0.117	0.015
Apply Q2 Odense						
Total Apps	762.941	751.000	nan	2557.157	2557.000	nan
constant	0.551	0.202	0.062	0.735	0.480	0.041
GPA	-0.061	-0.016	0.006	-0.091	-0.037	0.004
aar	-0.007	-0.014	0.012	0.078	0.051	0.008
ode	0.030	-0.002	0.011	-0.011	0.000	0.009
foreign	-0.020	-0.294	0.162	-0.126	-0.024	0.079
Pref NM over O	-0.048	-0.097	0.012	-0.100	-0.136	0.008
Apply Q1 CPH	0.084	-0.075	0.022	0.137	-0.111	0.014
Apply Q2 CPH	-0.014	0.108	0.015	-0.036	0.159	0.010
Prefer Ode to CPH	0.063	-0.008	0.025	0.137	0.013	0.015
Q2 App CPH but pref O	-0.012	0.149	0.028	0.006	0.086	0.017
Apply Q1 Aarhus	0.108	0.019	0.013	0.163	-0.027	0.009
Apply Q2 Aarhus	-0.033	0.132	0.014	-0.011	0.094	0.010
Prefer Ode to Aar	0.028	0.060	0.012	0.142	0.064	0.009
Q2 App Aar but pref O	-0.016	0.133	0.024	-0.008	-0.023	0.013

Note: This table presents estimates of the linear probability models outlined in equation 18. The first three columns analyze the pre-reform period 1994-2001 and the second three columns analyze the post-reform period, 2002-2013. The first column in each group denotes the estimates from the simulated, the second column denotes estimates on the data, and the third column presents the standard error on the point estimates in the data. The table is organized into three panels that analyze quota 2 applications to Aarhus, Copenhagen, and Odense, respectively.

Table 30: Counts of Placed Students and Quota 1 Applicants

	Pre		Post	
x	Model	Data	Model	Data
Placed Q1 Aarhus				
Odense Locals	139	145	176	179
Aarhus Locals	947	951	1847	1849
CPH Locals	299	300	1460	1462
Foreigners	61	55	325	331
Placed Q1 CPH				
Odense Locals	308	308	256	266
Aarhus Locals	182	182	206	213
CPH Locals	1592	1593	3420	3422
Foreigners	386	389	1015	1021
Placed Q1 Odense				
Odense Locals	415	427	481	481
Aarhus Locals	236	240	124	107
CPH Locals	347	348	596	595
Foreigners	100	99	397	399
Placed Q2 Aarhus				
Odense Locals	72	64	37	43
Aarhus Locals	456	454	317	324
CPH Locals	192	199	185	189
Foreigners	23	19	203	204
Placed Q2 CPH				
Odense Locals	75	70	35	38
Aarhus Locals	81	82	47	52
CPH Locals	742	743	634	636
Foreigners	38	33	66	66
Placed Q2 Odense				
Odense Locals	132	136	301	292
Aarhus Locals	94	94	359	361
CPH Locals	128	138	604	602
Foreigners	7	0	136	133
Q1 Applications				
10	749	558	1507	1516
12	263	565	1019	1341
13	422	275	1601	982
14	348	294	825	973
20	1938	1253	2653	2525
21	392	992	1177	1902
23	702	701	1993	1160
24	720	461	1838	1819
30	2764	2569	4886	4129
31	1099	1113	2394	3743
32	1322	1145	2941	2477
34	1344	1338	2655	2413
40	15391	15796	25328	25829
41	508	344	733	740
42	679	530	1497	1261
43	801	1102	2007	1700

Note: This table presents counts of placed students and quota 1 applicants. The first two columns analyze the pre-reform period 1994-2001 and the second two columns analyze the post-reform period, 2002-2013. The first column in each group denotes the estimates from the simulated data, the second column denotes estimates on the data. The table is organized into seven panels. The first size panels analyze placed quota 1 and quota 2 students at Aarhus, Copenhagen, and Odense, respectively, based on their former place of residence (e.g. students from the Odense region, "Odense Locals"). The last panel presents counts of quota 1 application to non-medical programs, organized by the top 2 priorities. "1" denotes Odense, "2" denotes Aarhus , 3 denotes Copenhagen, "4" denotes a non-medical programs, and "0" denotes none.

Table 31: Placed Students by Year

Year	Q1 C: M	Q1 C: D	Q1 O: M	Q1 O: D	Q1 A: M	Q1 A: D	Q2 A: M	Q2 A: D	Q2 C: M	Q2 C: D	Q2 O: M	Q2 O: D
1994	99	104	204	187	86	100	39	31	162	156	61	54
1995	113	137	282	310	140	130	99	105	122	122	48	52
1996	154	168	275	302	136	131	128	113	133	129	56	57
1997	130	127	329	299	132	139	126	124	125	122	43	55
1998	149	157	415	340	145	176	111	122	99	104	48	47
1999	232	231	326	348	160	120	77	69	107	107	39	36
2000	287	250	339	335	148	160	80	81	83	83	33	31
2001	283	277	298	351	150	158	83	91	105	105	34	36
2002	296	259	386	441	212	116	83	87	76	76	80	77
2003	326	263	321	428	169	117	83	91	84	86	103	103
2004	276	271	265	346	217	135	90	91	102	102	119	119
2005	313	271	302	411	146	134	79	86	79	81	119	121
2006	311	286	343	419	95	138	65	70	91	95	101	102
2007	249	317	429	357	88	145	73	75	101	103	114	113
2009	334	430	581	541	150	164	54	52	50	52	154	152
2010	422	458	534	476	152	156	52	53	54	53	146	145
2011	493	414	622	506	94	144	51	50	52	52	152	150
2012	392	420	571	515	199	165	56	52	49	49	149	149
2013	395	432	543	482	75	168	56	53	43	43	162	157

Note: This table denotes the number of placed students by quota, program and year. The rows denote the years. The 12 columns are divided into quota, program, and model versus data. Q1 abbreviates quota 1 and Q2 abbreviates quota 2. "C" abbreviates Copenhagen, "O" stands for Odense, and "A" stands for Aarhus. "M" stands for model, and indicates that the counts are calculated from the simulated data. "D" stands for data, and indicates that the counts are calculated from the data.

Table 32: Q2 Admitted Students by Year

Year	Q2 A: M	Q2 A: D	Q2 C: M	Q2 C: D	Q2 O: M	Q2 O: D
1994	63	41	196	182	69	72
1995	152	170	182	170	74	122
1996	182	193	184	182	79	110
1997	180	206	177	179	61	88
1998	181	231	170	139	76	125
1999	147	148	152	132	56	64
2000	164	127	120	103	51	80
2001	171	143	153	139	54	71
2002	185	150	125	109	87	130
2003	167	129	113	108	108	135
2004	163	145	126	140	125	162
2005	146	113	97	100	124	153
2006	123	98	109	115	105	140
2007	123	97	133	129	121	169
2009	105	113	65	57	165	207
2010	104	85	64	57	151	181
2011	112	105	65	56	161	181
2012	108	115	61	53	154	171
2013	105	100	50	45	166	205

Note: This table denotes the number of admitted quota 2 students by program and year. The rows denote the years. The 6 columns are divided into program and model versus data. Q2 abbreviates quota 2. "C" abbreviates Copenhagen, "O" stands for Odense, and "A" stands for Aarhus. "M" stands for model, and indicates that the counts are calculated from the simulated data. "D" stands for data, and indicates that the counts are calculated from the data.

Table 33: Q2 Admitted Students: LPM

	Pre			Post		
	Model	Data	SD Data	Model	Data	SD Data
Admitted to Aarhus						
constant	-1.214	-2.052	0.165	-0.254	-0.753	0.063
GPA	0.209	0.319	0.018	0.038	0.099	0.007
aar	0.044	0.004	0.024	0.041	0.052	0.013
ode	-0.061	-0.062	0.032	0.046	0.080	0.022
foreign	-0.066	-0.106	0.046	0.153	0.104	0.014
Pref NM over A	0.050	-0.051	0.030	0.085	-0.085	0.014
Aarhus First Pref	-0.051	0.006	0.012	0.035	0.033	0.006
Aarhus First Pref Among Q2 Apps	0.148	-0.020	0.048	0.055	-0.022	0.020
Q2 Admitted to Odense	-0.305	0.091	0.033	-0.097	0.073	0.021
Safe Admitted to Odense	0.237	-0.000	0.042	0.010	0.007	0.027
Q2 Admitted to CPH	-0.042	0.056	0.030	0.237	0.308	0.030
Safe Admitted to CPH	0.015	0.042	0.040	0.110	0.007	0.041
Admitted to CPH						
constant	0.458	0.114	0.069	0.705	0.342	0.033
GPA	-0.027	-0.000	0.007	-0.067	-0.030	0.003
aar	-0.047	-0.022	0.017	-0.001	-0.035	0.010
ode	-0.129	-0.079	0.016	-0.054	-0.049	0.011
foreign	-0.202	-0.124	0.016	-0.125	-0.098	0.006
Pref NM over C	0.006	-0.026	0.015	-0.080	-0.042	0.009
CPH First Pref	0.081	0.033	0.007	0.048	0.024	0.003
CPH First Pref Among Q2 Apps	-0.004	0.019	0.025	0.035	0.032	0.011
Q2 Admitted to Odense	-0.081	0.208	0.025	-0.060	0.089	0.012
Safe Admitted to Odense	0.024	-0.035	0.033	-0.003	0.091	0.016
Q2 Admitted to Aarhus	-0.053	0.211	0.023	0.079	0.119	0.014
Safe Admitted to Aarhus	0.026	-0.004	0.028	0.075	-0.005	0.018
Admitted to Odense						
constant	0.110	0.687	0.119	0.692	0.872	0.112
GPA	0.058	0.032	0.014	-0.013	-0.011	0.012
aar	-0.061	-0.002	0.015	0.145	0.036	0.020
ode	-0.061	-0.001	0.016	-0.124	-0.032	0.023
foreign	-0.374	0.011	0.054	-0.315	-0.082	0.029
Pref NM over O	-0.145	-0.046	0.030	0.071	-0.118	0.035
Odense First Pref	0.075	-0.005	0.024	0.046	0.053	0.038
Odense First Pref Among Q2 Apps	0.181	0.014	0.024	0.024	-0.033	0.038
Q2 Admitted to CPH	-0.032	0.027	0.018	0.030	0.087	0.034
Safe Admitted to CPH	0.006	0.008	0.021	-0.050	-0.000	0.044
Q2 Admitted to Aarhus	0.098	-0.031	0.016	0.084	0.086	0.037
Safe Admitted to Aarhus	0.081	0.038	0.019	0.012	-0.004	0.045

Note: This table presents estimates of the linear probability models outlined in equation 19. The first three columns analyze the pre-reform period 1994-2001 and the second three columns analyze the post-reform period, 2002-2013. The first column in each group denotes the estimates from the simulated, the second column denotes estimates on the data, and the third column presents the standard error on the point estimates in the data. The table is organized into three panels that analyze quota 2 admitted students to Aarhus, Copenhagen, and Odense, respectively.

Table 34: Top 50% of Q2 Admitted Students by Year

Year	Q2 A: M	Q2 A: D	Q2 C: M	Q2 C: D	Q2 O: M	Q2 O: D
1994	30	25	84	87	18	34
1995	78	82	86	84	74	62
1996	120	133	81	83	65	55
1997	114	116	81	81	28	41
1998	103	108	65	64	73	58
1999	69	64	58	59	23	31
2000	83	81	43	44	30	38
2001	98	98	65	66	29	35
2002	65	69	46	52	56	57
2003	109	109	41	45	63	64
2004	111	113	60	67	75	75
2005	90	93	41	45	72	71
2006	69	73	50	53	58	58
2007	77	80	58	62	76	74
2009	51	55	25	26	106	105
2010	38	42	27	28	91	90
2011	47	50	26	27	91	90
2012	53	56	25	26	86	85
2013	48	50	21	22	102	102

Note: This table denotes the number of safe admitted quota 2 students by program and year. These are students who are ranked in the top 50% among all students who received offers. The rows denote the years. The 6 columns are divided into program and model versus data. Q2 abbreviates quota 2. "C" abbreviates Copenhagen, "O" stands for Odense, and "A" stands for Aarhus. "M" stand for model, and indicates that the counts are calculated from the simulated data. "D" stands for data, and indicates that the counts are calculated from the data.

Table 35: Top 50% of Q2 Admitted Students: LPM

	Pre			Post		
	Model	Data	SD Data	Model	Data	SD Data
Safe Admitted to Aarhus						
constant	-2.466	-3.147	0.199	-0.205	-0.488	0.052
GPA	0.312	0.404	0.022	0.025	0.062	0.006
aar	0.066	0.042	0.029	0.027	0.029	0.011
ode	-0.092	-0.046	0.038	0.028	0.060	0.018
foreign	-0.142	-0.053	0.056	0.110	0.090	0.011
Pref NM over A	0.081	-0.108	0.036	0.053	-0.053	0.012
Aarhus First Pref	0.013	0.005	0.015	0.028	0.025	0.005
Aarhus First Pref Among Q2 Apps	0.083	0.019	0.058	0.034	-0.023	0.017
Q2 Admitted to Odense	-0.100	0.051	0.040	-0.049	0.050	0.017
Safe Admitted to Odense	0.157	-0.007	0.051	0.005	0.007	0.022
Q2 Admitted to CPH	-0.052	-0.037	0.037	0.150	0.170	0.025
Safe Admitted to CPH	0.028	0.123	0.048	0.100	0.032	0.034
Safe Admitted to CPH						
constant	0.229	0.064	0.050	0.337	0.166	0.024
GPA	-0.015	-0.005	0.005	-0.033	-0.015	0.003
aar	-0.027	-0.020	0.012	0.002	-0.011	0.007
ode	-0.067	-0.041	0.012	-0.023	-0.027	0.008
foreign	-0.100	-0.073	0.011	-0.057	-0.048	0.004
Pref NM over C	0.002	-0.007	0.011	-0.029	-0.029	0.006
CPH First Pref	0.044	0.026	0.005	0.028	0.011	0.002
CPH First Pref Among Q2 Apps	-0.005	0.036	0.018	0.016	0.017	0.008
Q2 Admitted to Odense	-0.042	0.157	0.018	-0.029	0.044	0.009
Safe Admitted to Odense	0.011	-0.009	0.024	-0.003	0.058	0.011
Q2 Admitted to Aarhus	-0.031	0.098	0.017	0.032	0.054	0.010
Safe Admitted to Aarhus	0.015	0.042	0.020	0.045	0.008	0.013
Safe Admitted to Odense						
constant	-0.114	-0.661	0.373	0.429	0.558	0.134
GPA	0.057	0.123	0.043	-0.010	-0.024	0.015
aar	-0.060	-0.089	0.046	0.161	0.035	0.025
ode	-0.069	-0.027	0.049	-0.113	-0.021	0.028
foreign	-0.271	-0.253	0.169	-0.246	-0.064	0.034
Pref NM over O	-0.097	-0.242	0.095	0.066	-0.077	0.042
Odense First Pref	0.056	0.008	0.076	0.035	0.154	0.046
Odense First Pref Among Q2 Apps	0.170	0.160	0.076	0.020	-0.120	0.046
Q2 Admitted to CPH	-0.011	-0.030	0.057	0.024	0.147	0.041
Safe Admitted to CPH	0.010	0.032	0.067	-0.046	0.039	0.053
Q2 Admitted to Aarhus	0.092	0.087	0.051	0.079	0.066	0.044
Safe Admitted to Aarhus	0.111	0.024	0.060	0.008	0.007	0.054

Note: This table presents estimates of the linear probability models outlined in equation 20. The first three columns analyze the pre-reform period 1994-2001 and the second three columns analyze the post-reform period, 2002-2013. The first column in each group denotes the estimates from the simulated, the second column denotes estimates on the data, and the third column presents the standard error on the point estimates in the data. The table is organized into three panels that analyze quota 2 safe admitted students to Aarhus, Copenhagen, and Odense, respectively. Safe admitted students are those who are ranked in the top 50% among all students, who received offers.

Table 36: Persist: LPM

	Pre			Post		
	Model	Data	SD Data	Model	Data	SD Data
Persistence at Aarhus						
constant	0.681	0.350	0.200	0.526	0.275	0.105
GPA	0.012	0.034	0.021	0.022	0.037	0.011
aar	-0.011	0.034	0.022	0.013	0.015	0.013
ode	-0.020	0.014	0.034	0.016	-0.019	0.029
foreign	-0.352	-0.337	0.052	-0.391	-0.320	0.021
Pref NM over A	-0.269	-0.313	0.057	-0.086	-0.100	0.047
Aarhus First Pref	0.040	0.038	0.018	0.075	0.075	0.010
Apply Q2 Aarhus	0.059	0.225	0.094	-0.032	-0.041	0.018
Q2 Admitted to Aarhus	-0.067	-0.185	0.093	0.102	0.128	0.027
Safe Admitted to Aarhus	0.001	0.001	0.029	0.054	-0.005	0.026
Q2 Admitted to Odense	0.047	-0.045	0.053	0.014	-0.057	0.045
Safe Admitted to Odense	0.039	0.058	0.073	0.012	0.153	0.063
Q2 Admitted to CPH	0.092	0.098	0.056	0.022	0.061	0.071
Safe Admitted to CPH	0.020	0.017	0.077	-0.017	-0.066	0.101
Persistence at Odense						
constant	0.551	0.237	0.275	0.506	0.590	0.113
GPA	0.016	0.039	0.030	0.029	0.017	0.011
aar	-0.037	-0.006	0.032	0.012	0.030	0.021
ode	0.072	0.050	0.030	0.021	0.046	0.018
foreign	-0.197	-0.143	0.051	-0.327	-0.303	0.020
Pref NM over O	-0.268	-0.232	0.067	-0.134	-0.090	0.048
Odense First Pref	0.049	0.051	0.028	0.019	0.011	0.016
Apply Q2 Odense	-0.210	-0.188	0.324	0.000	0.170	0.087
Q2 Admitted to Aarhus	-0.017	-0.037	0.061	0.025	0.038	0.044
Safe Admitted to Aarhus	0.036	0.168	0.079	-0.012	0.006	0.056
Q2 Admitted to Odense	0.283	0.340	0.325	0.101	-0.066	0.089
Safe Admitted to Odense	0.030	0.009	0.043	0.014	0.035	0.020
Q2 Admitted to CPH	0.088	0.121	0.083	0.032	0.064	0.067
Safe Admitted to CPH	0.020	-0.088	0.113	-0.015	-0.046	0.088
Persistence at CPH						
constant	0.333	0.418	0.160	0.765	0.641	0.115
GPA	0.044	0.037	0.016	0.006	0.014	0.010
aar	-0.056	-0.062	0.030	0.032	-0.001	0.025
ode	-0.025	-0.013	0.024	-0.022	-0.078	0.024
foreign	-0.500	-0.482	0.025	-0.486	-0.440	0.018
Pref NM over C	-0.202	-0.166	0.044	-0.225	-0.291	0.067
CPH First Pref	0.007	-0.006	0.018	-0.002	0.009	0.018
Apply Q2 CPH	-0.020	-0.022	0.019	-0.001	-0.047	0.017
Q2 Admitted to Aarhus	0.045	0.044	0.048	0.052	0.050	0.039
Safe Admitted to Aarhus	-0.021	0.052	0.060	-0.022	-0.034	0.049
Q2 Admitted to Odense	0.108	0.136	0.051	0.083	0.114	0.042
Safe Admitted to Odense	-0.001	-0.072	0.075	0.008	-0.000	0.054
Q2 Admitted to CPH	0.082	0.078	0.027	0.039	0.034	0.026
Safe Admitted to CPH	0.040	0.008	0.028	0.022	0.074	0.027

Note: This table presents estimates of the linear probability models outlined in equation **??**. *The first three columns analyze the pre-reform period 1994-2001 and the second three columns analyze the post-reform period, 2002-2013. The first column in each group denotes the estimates from the simulated, the second column denotes estimates on the data, and the third column presents the standard error on the point estimates in the data. The table is organized into three panels that analyze persistence Aarhus, Copenhagen, and Odense, respectively.*

Table 37: GPA

	Pre		Post	
	Model	Data	Model	Data
Mean GPA: Persisting Students at AAR				
Odense Locals	9.46	9.48	9.86	9.75
Aarhus Locals	9.46	9.45	9.96	9.93
Danish Locals	9.37	9.29	10.04	10.14
Foreigners	9.48	9.16	9.58	9.70
Mean GPA: Not Persisting Students at AAR				
Odense Locals	9.38	9.34	9.91	9.73
Aarhus Locals	9.35	9.37	9.99	9.86
Danish Locals	9.22	9.30	10.03	9.99
Foreigners	9.44	9.42	9.56	9.71
Mean GPA: Persisting Students at Ode				
Odense Locals	9.12	9.18	9.33	9.53
Aarhus Locals	9.00	9.08	8.89	9.00
Danish Locals	9.01	9.02	9.26	9.42
Foreigners	9.24	9.23	9.41	9.47
Mean GPA: Not Persisting Students at Ode				
Odense Locals	9.21	9.27	9.48	9.58
Aarhus Locals	9.05	9.15	8.88	9.11
Danish Locals	9.11	9.00	9.33	9.45
Foreigners	9.29	9.30	9.53	9.81
Mean GPA: Persisting Students at CPH				
Odense Locals	9.66	9.66	10.12	10.00
Aarhus Locals	9.47	9.41	10.15	10.03
Danish Locals	9.49	9.46	10.22	10.12
Foreigners	9.85	9.72	10.26	10.08
Mean GPA: Not Persisting Students at CPH				
Odense Locals	9.65	9.60	10.22	9.89
Aarhus Locals	9.46	9.43	10.23	9.90
Danish Locals	9.43	9.45	10.30	10.06
Foreigners	9.83	9.79	10.29	10.21

Note: This table presents the mean GPA across different populations. The first two columns analyze the pre-reform period 1994-2001 and the second two columns analyze the post-reform period, 2002-2013. The table is organized into six panels dividing the student population into those who persist (enroll and do not drop out within the first three years) and those who do not persist by program. "Aar" abbreviates Aarhus, "Ode" stands for Odense and "CPH" stands for Copenhagen. Each panel breaks out the student population by their former place of residence (e.g. students from the Odense region, "Odense Locals").

Table 38: Persistence Counts

	Pre		Post	
	Model	Data	Model	Data
Persist at Aarhus				
Q1 Aar All	1133.31	1109.00	2900.87	2913.00
Q2 Aar All	542.76	576.00	558.77	538.00
Odense Locals	156.00	159.00	170.80	167.00
Aarhus Locals	1116.88	1122.00	1775.00	1771.00
CPH Locals	369.93	374.00	1291.37	1290.00
Foreigners	33.27	30.00	222.47	223.00
Persist at CPH				
Q1 CPH All	1664.14	1657.00	3402.45	3409.00
Q2 CPH All	700.51	713.00	644.34	628.00
Odense Locals	282.05	282.00	225.38	220.00
Aarhus Locals	187.21	185.00	209.54	210.00
CPH Locals	1786.49	1787.00	3254.37	3254.00
Foreigners	108.90	116.00	357.50	353.00
Persist at Odense				
Q1 Ode All	739.86	719.00	1130.87	1126.00
Q2 Ode All	285.16	299.00	1172.17	1184.00
Odense Locals	429.44	420.00	657.78	665.00
Aarhus Locals	228.21	225.00	407.12	407.00
CPH Locals	320.72	325.00	980.77	980.00
Foreigners	46.64	48.00	257.37	258.00

Note: This table presents persistence counts across different populations. The first two columns analyze the pre-reform period 1994-2001 and the second two columns analyze the post-reform period, 2002-2013. The table is organized into three panels dividing the student population into those that persist at Aarhus, Copenhagen and Odense, respectively. Each panel first breaks up the student population by quota, where "Q1" denotes quota 1 and "Q2" denotes quota 2. It next breaks up students (quota 1 and quota 2 students) by their former place of residence (e.g. students from the Odense region, "Odense Locals").