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.

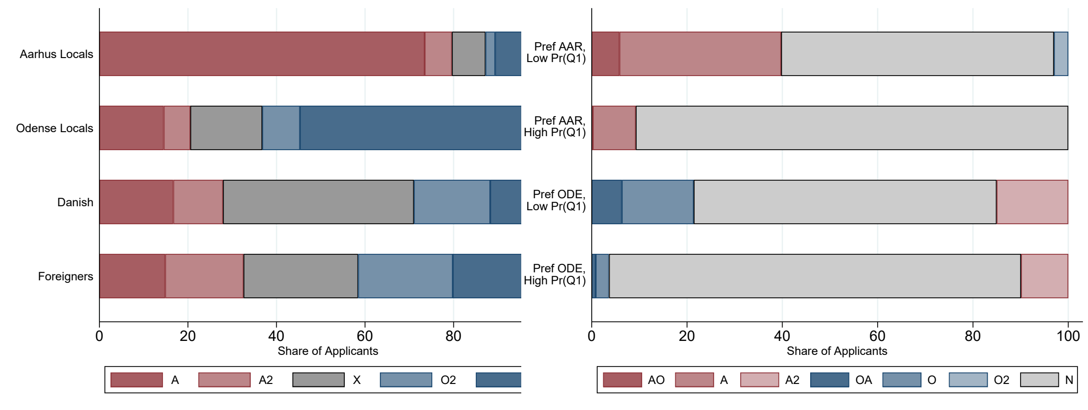
We note three insights from this figure. First, Copenhagen is most popular among applicants, but only in regions outside of Odense and Aarhus. Second, in counties close to Odense, Odense is the most popular program, whereas Aarhus is by far the most preferred program in counties close to Aarhus. In addition,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

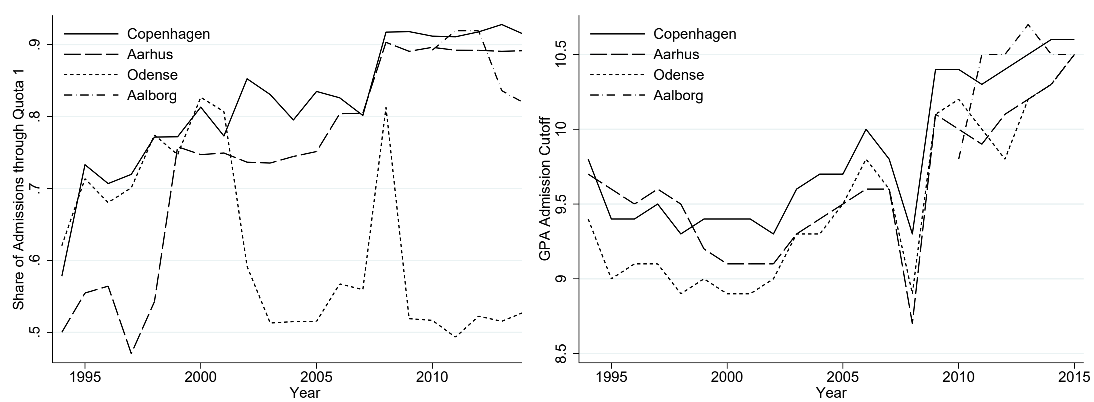


(a) Preferences by Former Residence (b) Quota 2 Applications

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

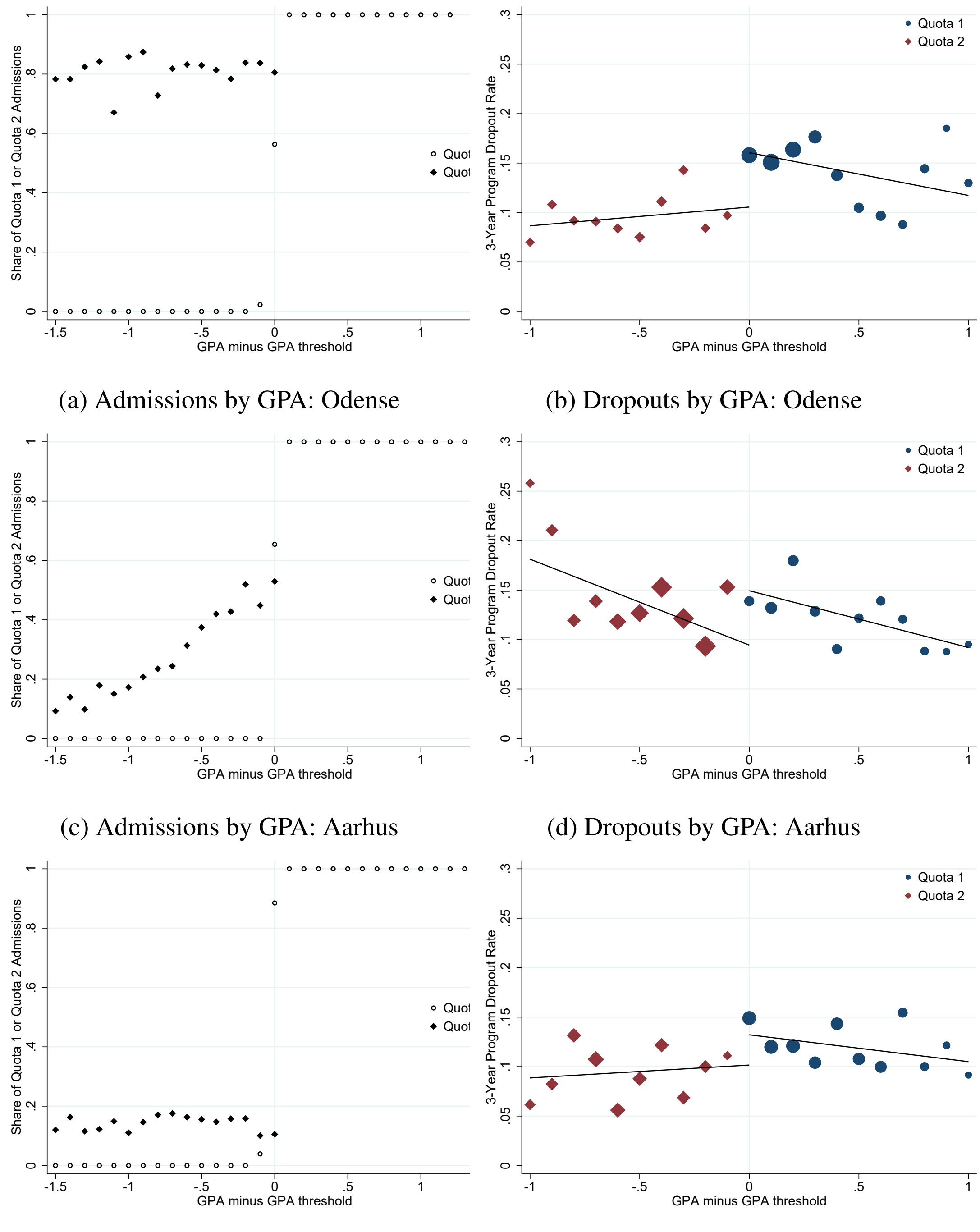
Figure 8 complements the evidence in Figure 1 and Table 2. The evidence in the left panel shows the discontinuity in admission chances at the GPA threshold. In addition, Quota 2 admission chances increase substantially with GPA at Aarhus, but are constant across a wide GPA range at Odense and Copenhagen. 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.

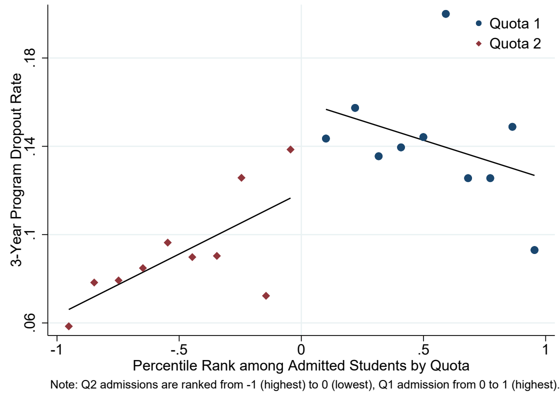
We formalize these findings in Table 12 by estimating the differences in dropout rates among enrolled students at each program according to their position on the program's ranking for admissions. To also compare marginal students admitted through Quota 1 and Quota 2, we estimate regression-discontinuity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

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

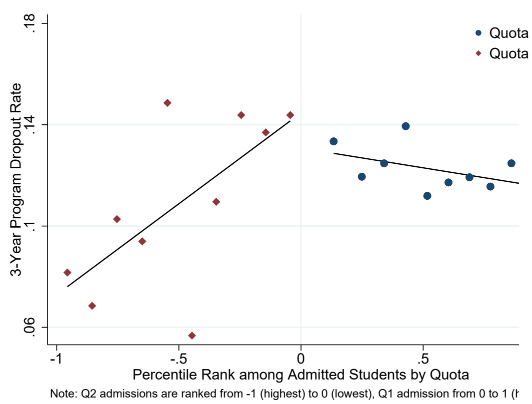
where $perc_i \in [0, 1]$ is the percentile rank of student i in their admission quota. We control for linear trends in the rankings for Quota 1 and Quota 2 students. The key parameter of interest is γ_s, which denotes the discontinuous change in dropout rates when going from quota 1 to quota 2. Graphically, 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.

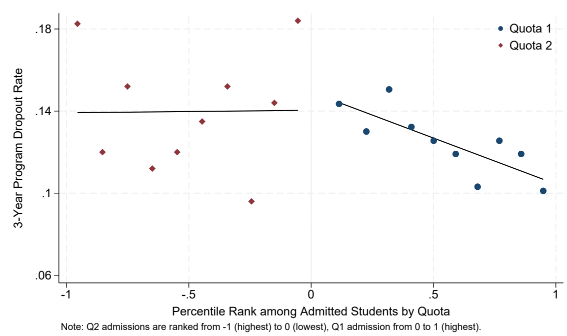
Figure 9: Dropouts by Rank within Quota



(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

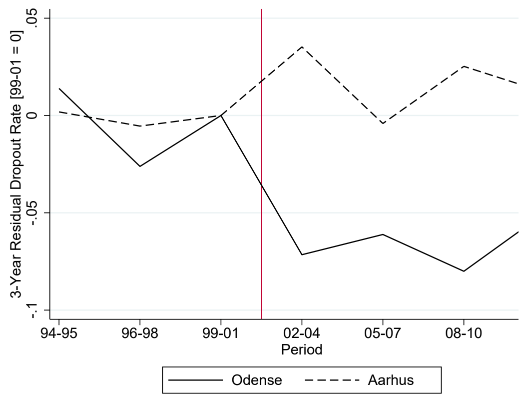
Note: Panel A of Table 5 analyzes Copenhagen's and Odense's relative quota 2 rankings for pairs of quota 2 applicants to both programs, while Panel B analyzes pairs of quota 2 applicants to Copenhagen, Aarhus, and Odense. "ODE Ranks 1>2" is an indicator variable that takes value 1 if Odense assigns a 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.

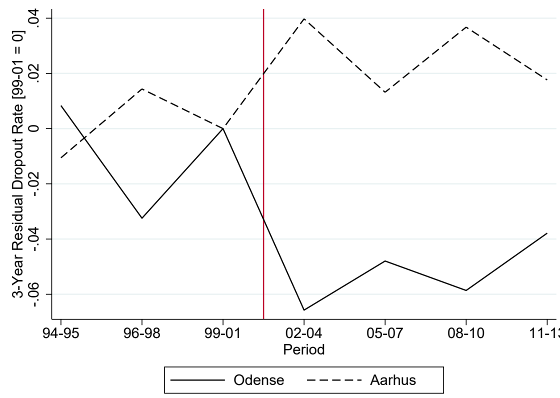
A.5 Details on Self-Selection and Quota 2 Admissions

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.

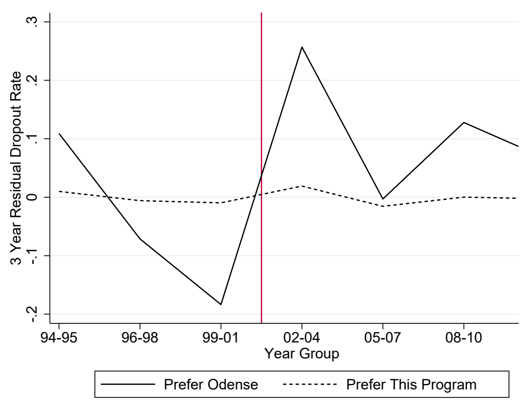
Figure 10: Dropout Rates by Medical Program Over Time



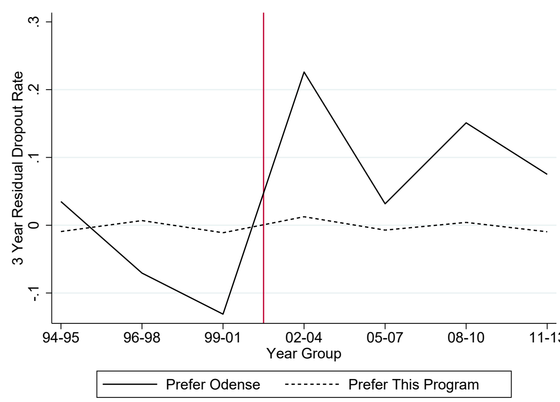
(a) Program-Specific 3-Year Dropout



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



(c) Program-Specific 3-Year Dropout



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

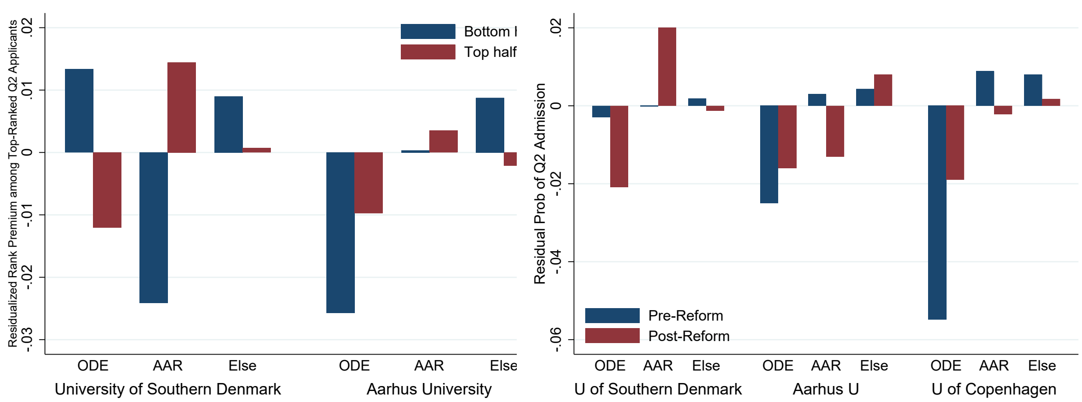
Note: Figures 10a and 10c plot the program-specific 3-year dropout rate of enrolled students to Aarhus and Odense over time, while Figure 10b and 10d measure all dropouts, including transfers within the first three years of study or before the first BA degree, whichever comes first. The vertical axis 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) Prog 1y	(2) Prog 3y	(3) Med 1y	(4) Med 3y	(5) Completion	(6) 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,

$$\begin{aligned} n_{med} = \tilde{\gamma}^{nm}_{0} + \sum_{l} \tilde{\gamma}^{nm}_{l} \mathbb{1}\{loc_i = l\} + \tilde{\gamma}^{nm}_{gpa} GPA_{it} \\ + \tilde{\gamma}^{nm}_{a} \mathbb{1}\{app^{aar}_{it}\} \mathbb{1}\{app^{ode}_{it} = 0\} + \tilde{\gamma}^{nm}_{o} \mathbb{1}\{app^{ode}_{it}\} \mathbb{1}\{app^{aar}_{it} = 0\} \\ + \tilde{\gamma}^{nm}_{ao} \mathbb{1}\{app^{ode}_{it}\} \mathbb{1}\{app^{aar}_{it}\} \mathbb{1}\{AAR \succ ODE\} \\ + \tilde{\gamma}^{nm}_{oa} \mathbb{1}\{app^{ode}_{it}\} \mathbb{1}\{app^{aar}_{it}\} \mathbb{1}\{ODE \succ AAR\} \\ + \tilde{\gamma}^{nm}_{c} \mathbb{1}\left\{app^{cph}_{it}\right\} + \tilde{\gamma}^{nm}_{c1} \mathbb{1}\left\{app^{cph}_{it}\right\} \mathbb{1}\{r(cph) = 1\} + \tilde{\gamma}^{nm}_{c2} \mathbb{1}\left\{app^{cph}_{it}\right\} \mathbb{1}\{r(cph) = 2\} \end{aligned} \tag{16}$$

Third, we use linear probability models to match the probability of quota 2 application y^{q2}_{ijt} 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).

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

Fourth, we use linear probability models to match the probability of receiving a potential offer adm^{q2}_{ijt}, 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).

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

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.

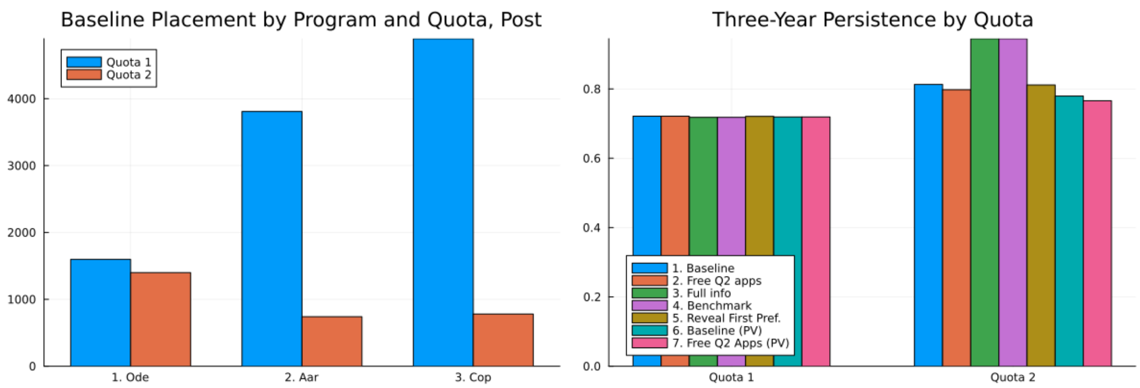
Quota 1 and Quota 2 Students As noted in the main text, we focus our analysis on quota 2 students. The left graph of Figure 12 presents annual placements by quota and program to give context. The right graph presents select counterfactual persistence rates, detailed further below, by quota. There are 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.

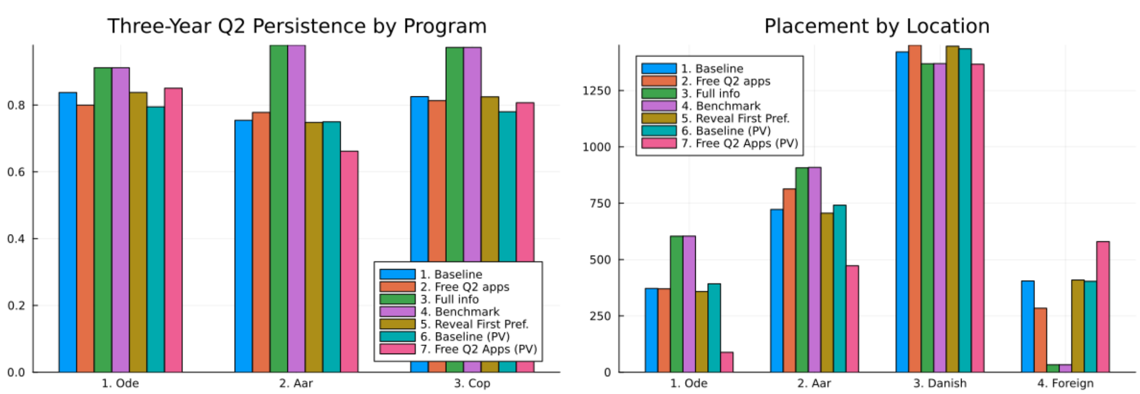
Second, we quantify the scope for improvements in the outcome of interest (3-year

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) $\mathbb{1}\{$non-med first$\}$	(2) Pr(persist)	(3) $\mathbb{1}\{$non-local first$\}$	(4) Pr(persist)	(5) $\mathbb{1}\{$foreign first$\}$	(6) 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 × first-pref		0.0033***				
		(0.001)				
non-local first				0.0931***		
				(0.006)		
non-local first × first-pref				0.0006		
				(0.004)		
foreign						-0.0606***
						(0.008)
foreign × 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.