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

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We ask: (1) How do firms (higher-ed programs) compete for students in presence of interdep. values? (2) How does the presence of interdep. values—and programs' responses to this situation—affect production?

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    - Institutions and natural experiment allow us to test for / quantify sources of interdependent values:
        - Interdependent program values: winner's curse when candidates are rejected by competitors.
        - match effects / college like people who like them (Avery and Levin, AER 2010)
        - (Relatedly) self-selection when applications are costly (Chade, Lewis, Smith, REstud 2014).

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2. Analyze the effects of imperfect information and interdependent values in an empirically important setting.

Context: Medical schools in Denmark

- 5 years of training (finish w/ Master's degree followed by residency training)
- Students apply directly after high school
- 3 programs: Copenhagen, Aarhus, and Odense (Aalborg from 2010)
- Admissions via centralized matching procedure (CPDA) in which both sides express preferences.
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- Dropout is a concern for public, students, programs:
  - High dropout rates ($15 - 20\%$) are major concern: wasted time + resources.
  - Associated with struggling academically (O'Neill 2011).
  - 80% of university funding uses a "taximeter" scheme (passed exams weighted by course study time)

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- Policy change: information experiment

Related Literature

Models of matching markets:

- Large literature starting with Gale and Shapley (AMM 1962): existence and properties of stable matching; DA algorithm, SOSM mechanism.
- Azevedo and Leshno (JPE 2016): large-market model (continuum of students, N programs).
- Chakraborty, Citanna, Ostrovsky (JET 2010): Nonexistence of stable matching mechanism with interdependent values.
- Chade et al. (REStud 2014): model of college admissions with common values in a decentralized setting and many agents

- Che and Koh (JPE 2016): aggregate preference shocks and yield-management concerns.
- Friedrich (2016): Dynamics, young workers less adversely selected than older movers.
- Avery and Levin (AER 2010): colleges like people who like them; EA/ED finds these people.
- Lee (IER 2010): common values, early decision (ED) as specific technology to address winner's curse.

Our novelty: interdependent program values + preference signals in matching setting.

Interdependent Values: Key Intuition

Suppose program 1 considers two candidates, A and B, who look the same after interviews, tests,...

- A: "You are my Nth choice. I'll accept your offer if the other programs reject me."
- B: "If you make me an offer, I will accept it. Here is evidence..."

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Self-Selection: Student preferences pos. associated with program payoff

- All else equal, program 1 should prefer B.
- Program 1's screening efforts raise application costs $\implies$ ambiguous effects on selection.

Context: Program Admissions

Two ways to get in:

- **Quota 1:** Applicants (passively) ranked by high school GPA:
  - 50-70% of seats allocated to quota 1 admissions
- **Quota 2:** Programs rank applicants on a broader set of characteristics:
  - E.g. subject grades, motivation letter, tests or personal interviews
  - Admission criteria and review efforts differ between programs
- Assignment via college-proposing DA algorithm:
  - Students fill out ROL with Quota-1 apps, check box next to program for Quota 2 if desired and provide additional materials.
  - Each program is divided into Q1 and Q2 pseudoprograms.
  - If apply Q2 to program j, insert j-Q2 pseudoprogram into ROL just after j-Q1.
  - Number of seats, share Q2 seats is regulated (programs would like more students).

Example: Q1 and Q2 Application

	Quota 1:
Medicine Aarhus:	1
Medicine Odense:	2
Dentistry Aarhus:	3
Math Copenhagen:	4

Example: Q1 and Q2 Application

	Quota 1:	Quota 2:
Medicine Aarhus:	1	✓
Medicine Odense:	2	X
Dentistry Aarhus:	3	✓
Math Copenhagen:	4	X

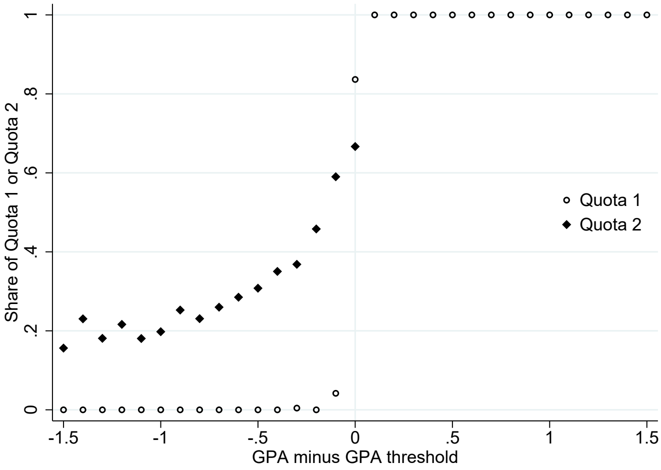
Example: Q1 and Q2 Application

	Quota 1:	Quota 2:	Extended ROL
Medicine Aarhus:	1	✓	1
Medicine Odense:	2	X	1.2
Dentistry Aarhus:	3	✓	2
Math Copenhagen:	4	X	3
			3.2
			4

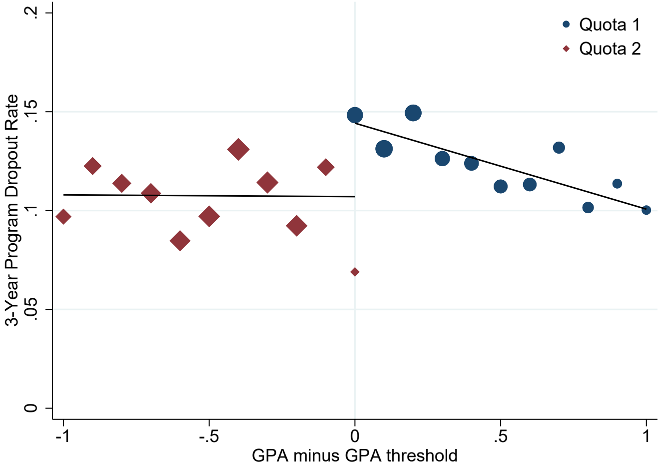
Sample: Medical School Applicants

	Copenhagen	Aarhus	Odense
# Applicants	30,356	25,328	22,497
Preferences and Quota 2 Applications			
Share listing j as 1st Priority	0.682	0.438	0.289
Share listing j as 1st Priority: Aarhus Locals	0.276	0.726	0.222
Share listing j as 1st Priority: Odense Locals	0.483	0.252	0.641
Share submitting Quota 2 Application to j	0.616	0.34	0.155
Share submitting Quota 2 Application to j: high GPA	0.353	0.124	0.025
Admissions and Outcome			
# Admitted	9,475	6,949	4,680
# Enrolled	7,885	6,049	4,093
1y Dropout Rate	0.05	0.055	0.05
3y Dropout Rate	0.121	0.128	0.119
3y Transfer Rate	0.005	0.011	0.016
10y Completion Rate	0.832	0.842	0.831
Sample Years	1994-2013	1994-2013	1994-2013

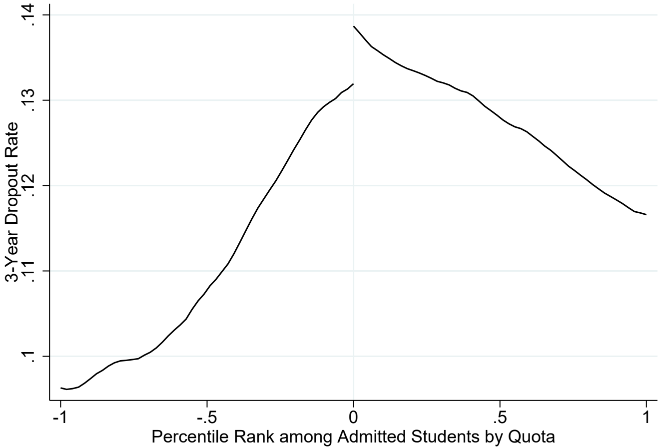
Less likely to get in below GPA cutoff



Q2 Applicants Less Likely to Drop Out



Dropout rate by Q1/Q2 ranking



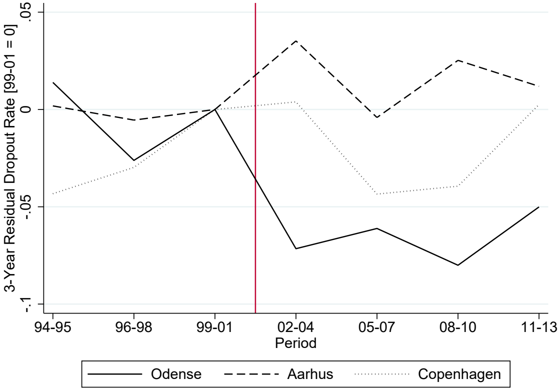
Note: Q2 admissions are ranked from -1 (highest) to 0 (lowest), Q1 admission from 0 to 1 (highest).

Odense's Admission Reform in 2002

In 2002, Odense's faculty of health sciences changed their admission process:

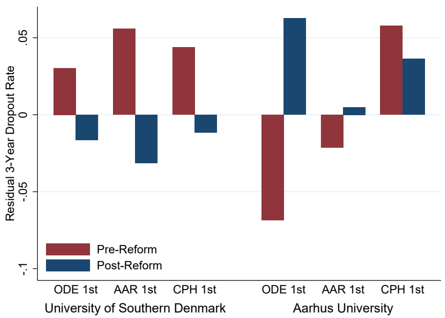
- Motivated in parts b/c of high dropout rates and to attract highly motivated students
- High applicant to seat ratio (6 to 1) pre 2002, yet 70% were admitted purely on the basis of the GPA
- Lower quota 1 share to 50%
- Increase review criteria for quota 2 admissions [25 min interview, motivational essay, admission test]
- No changes to curriculum or study program itself

Dropouts and Odense's Admission Reform



- Odense's dropout rate falls by 7.1 p.p. (after admission reform) ▸ Table

Dropouts at Aarhus and Odense's Reform



- Programs cannot condition admissions on preferences ‣ Table
- Students who prefer & enroll at Aarhus not affected (control group)
- Students who prefer Odense & enroll at Aarhus are adversely selected after reform; dropout rate increases by 12.3 p.p. ‣ Fig

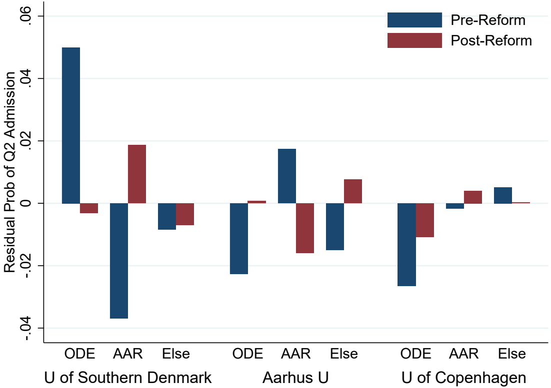
Program Rankings and Dropouts

Outcome	(1) AAR 1>2	(2) Difference in 3Y Dropout for Student 1 versus Student 2	(3)	(4)	(5)
Sample	All	All	Both ODE	None ODE	All
ODE Ranks 1>2	0.059***	-0.116***	-0.030*	-0.061**	-0.051
	(0.017)	(0.018)	(0.017)	(0.025)	(0.039)
AAR Ranks 1>2		-0.020	-0.019	-0.039	-0.009
		(0.015)	(0.017)	(0.025)	(0.035)
ODE Ranks 1>2 Post					-0.073*
					(0.043)
AAR Ranks 1>2 Post					-0.012
					(0.038)
Observations	70,044	70,044	22,312	15,156	70,044
R-squared	0.035	0.053	0.084	0.075	0.054

- Outcome: 1 if candidate 1 drops and 2 doesn't; 0 if both or none drop out; -1 if candidate 2 drops and 1 doesn't
- Odense's ranking predicts dropouts conditional on Aarhus' ranking
- Evidence for interdependent program values

Programs Exhibit Home Bias

And adjust as expected post-reform



- Odense reduces home bias post-reform
- Aarhus shifts bonus towards students from other regions

Descriptive analysis: Summary

1. Quota-2 (discretionary) application and admissions decisions together contain info about dropout.
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Next: rationalize these facts with equilibrium model, investigate counterfactuals.

Model Overview

Students: On the student side, we model:

- Imperfect information about talents and admissions chances
- Preferences over programs (based on GPA & location, correlated with talents and signals)
- Quota 1 and Quota 2 application decisions based on preferences and (in the case of Quota 2) application costs and chances of success

Programs: On the program side, we model:

- Private signals about talents
- Quota 2 admissions rules
- Dropout/persistence.

Agents and Information

- Three "inside" options (Ode, Aar, Cop): $j \in \{1, 2, 3\}$ with $m_j^k \in \mathbb{R}_+$ quota-k seats
- Continuum of students; each characterized by type vector

$$(X, \mathrm{u}, \omega, \mathrm{s}, \mathrm{c})$$

Preferences, costs, signals distributed according to $Pr(x, u, s, c) = Q(x)F(u, s, c|x)$. Program payoffs have distributions $F_j(\omega_j|u, s, c, x)$ for $j = 1, 2$.

  - X: finite set of **commonly observed** variables (GPA, location).
  - $u_j \in \mathbb{R}$: student's utility if match to j, **private to the student.**
  - $\omega_j \in \mathbb{R}$: j's payoff from matching with i, **no one observes.**
  - $s_j \in \mathbb{R}$ signal of ω_j, **private to j.**
  - $c_A \in \mathbb{R}$, $A = \{1\}, \{2\}, \dots, \{1, 2, 3\}$: quota 2 application costs for set A, **private to the student.**

Strategies, Timing, Payoffs

- Each student observes own (X, u, c), decides Quota-1 ROL & for programs on list, whether to apply via Quota 2.

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$$r_j : X \times \mathbb{R} \to [0, 1]$$

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- Medical programs get ω_{ij} from each student who enrolls. Details

Analysis

Students maximize expected utility by choice of Quota 1 apps (free), Quota 2 apps (costly)

- Quota 1 apps: truthful (large mkt).
- Q2 apps: depends on u, app costs, program strategies. Details

Medical Programs are assumed to rank applicants by expected value conditional on accepting the offer.

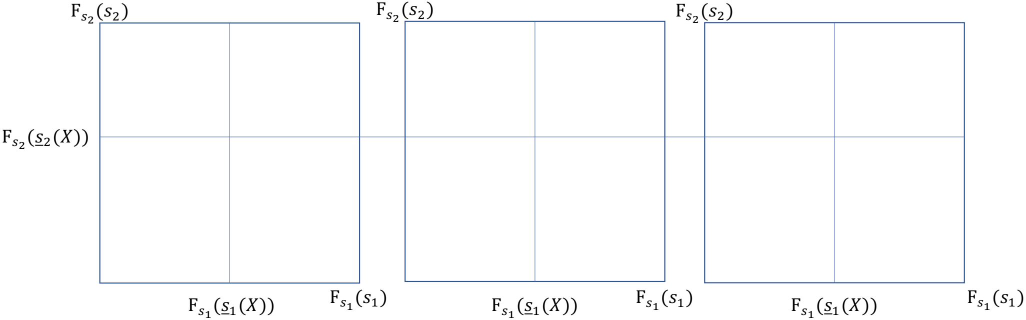
1. Theory: MLRP + conditional independence $\implies$ rankings are monotone in signals. (cutoffs!)
2. Empirics: relax CI assumption but *restrict to* monotone strategies; then verify.

On-platform outside option: best non-medical program (j=4):

- A student may include it in Q1 ROL, receives u_4 if placed, but...
- We don't model Q2 apps or admissions for this program.
- Admissions chance depends on observables only: $Pr(\text{admit}_4|X) = \Phi(X'\beta_o)$.

Pick a value of X

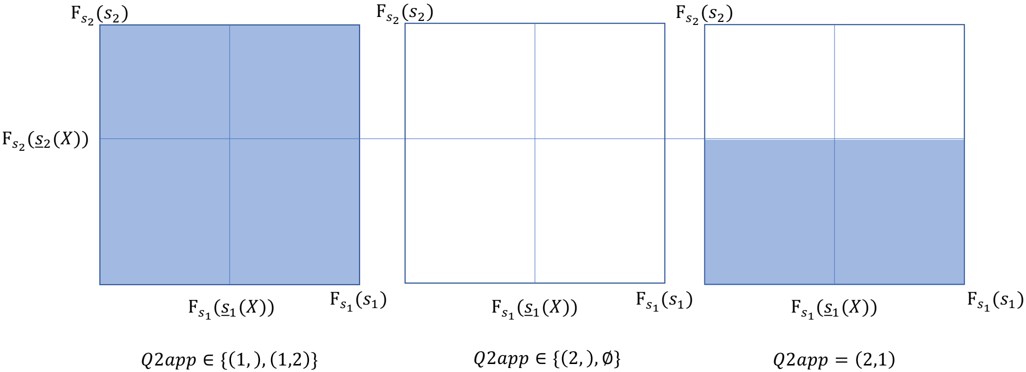
Suppose program rankings r_j are monotone in s_j for this X.



$Q2app \in \{(1,),(1,2)\}$ $\quad$ $Q2app \in \{(2,),\emptyset\}$ $\quad$ $Q2app = (2,1)$

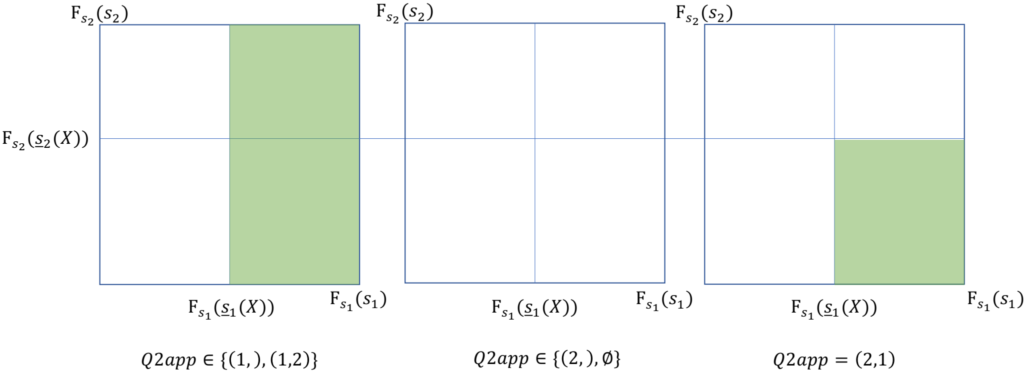
$D_1^2(X, \underline{s})$

Set of people with observables X available to program 1 via quota 2.



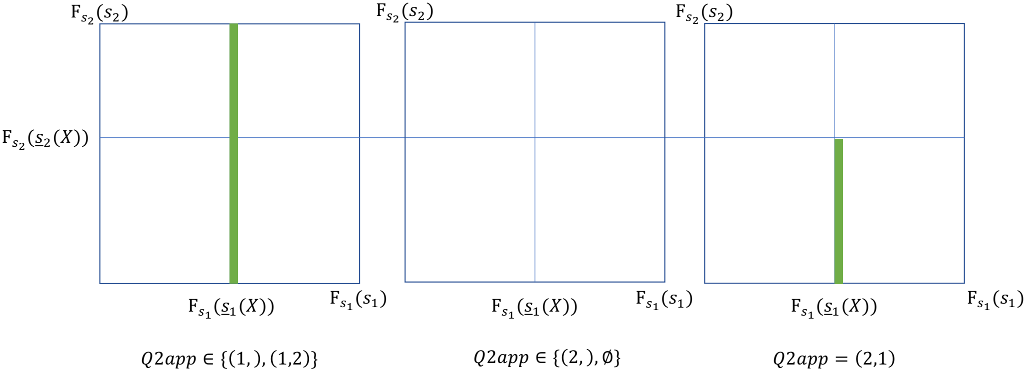
Enrolled students

Match to $j = 1$ if in $D_1^2(x, \underline{s})$ and $s_1 > \underline{s}_1(X)$.



Students at the margin

To solve model, need to find cutoff functions $\underline{s}_j : \mathcal{X} \to \mathbb{R}$.



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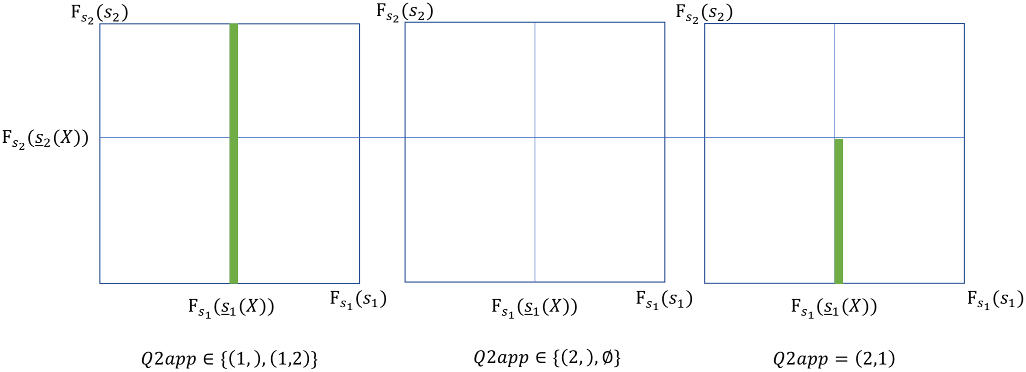
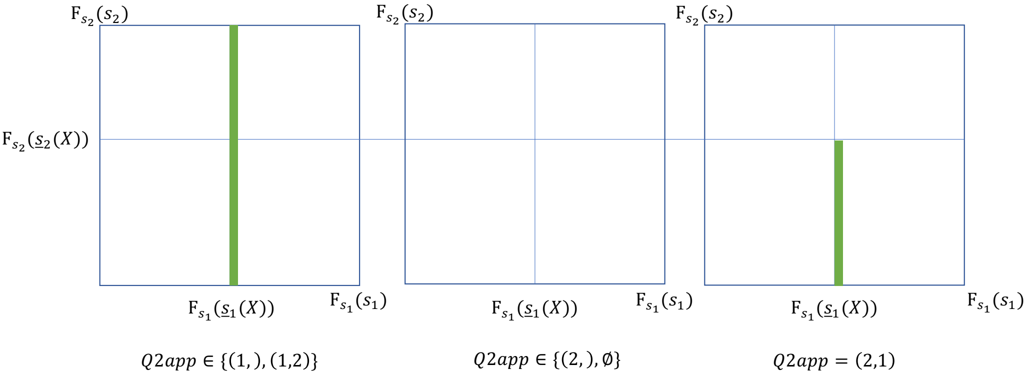
Optimality requires: $\underline{s}_j(\cdot)$ satisfies cap. constraint, and "EV at margin" equated at all X's.



Students at the margin

"EV at margin": $E(\omega_{ij}|s_{ij} = \underline{s}_j(X), i \in D_j^2(X, \underline{s})) = \underline{\omega}_j \ \forall X$ for some $\underline{\omega}_j$.



Empirical Model

Parametric assumptions for estimation:

- Utility shocks, signals $(\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, s_1, s_2, s_3)$ jointly normal $\sim N(0, \Sigma)$.

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- Linear index for utility at j: $u_j = x\gamma_j + \epsilon_j$.
- Potential outcome (persistence at j): $\omega_j^* = 1(x\alpha_j + \tilde{\omega}_j > 0)$.
- We specify marginal dist. of unobs. persistence shock at j:

$$\tilde{\omega}_j|\epsilon, s \sim N\left(\rho_j' \Sigma^{-1} \left(\varepsilon_1, \varepsilon_2, s_1, s_2\right)', 1 - \rho_j' \Sigma^{-1} \rho_j\right).$$

Consistent w/ joint normality of $u, s, \tilde{\omega}$ with $var(\tilde{\omega}_j) = 1$. But we do not specify $\mathrm{cov}(\tilde{\omega}_j, \tilde{\omega}_k)$.

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- Utility shocks, signals $(\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, s_1, s_2, s_3)$ jointly normal $\sim N(0, \Sigma)$.
- Quota-2 app costs (c_1, c_2, c_3) jointly normal, $\perp \varepsilon, s$.
- Linear index for utility at j: $u_j = x\gamma_j + \epsilon_j$.
- Potential outcome (persistence at j): $\omega_j^* = 1(x\alpha_j + \tilde{\omega}_j > 0)$.
- We specify marginal dist. of unobs. persistence shock at j:

$$\tilde{\omega}_j | \epsilon, s \sim N\left(\rho_j' \Sigma^{-1} \left(\varepsilon_1, \varepsilon_2, s_1, s_2\right)', 1 - \rho_j' \Sigma^{-1} \rho_j\right).$$

  Consistent w/ joint normality of $u, s, \tilde{\omega}$ with $var(\tilde{\omega}_j) = 1$. But we do not specify $\text{cov}(\tilde{\omega}_j, \tilde{\omega}_k)$.
- Important restriction: graduation parameters α fixed across periods (other parameters vary pre/post).

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- Program payoffs = Pr(persist) + **non-grad. prefs**: $\omega_j = \omega_j^* + \pi_j(x)$.

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- In practice, extract additional info from program ROLs.

Estimates

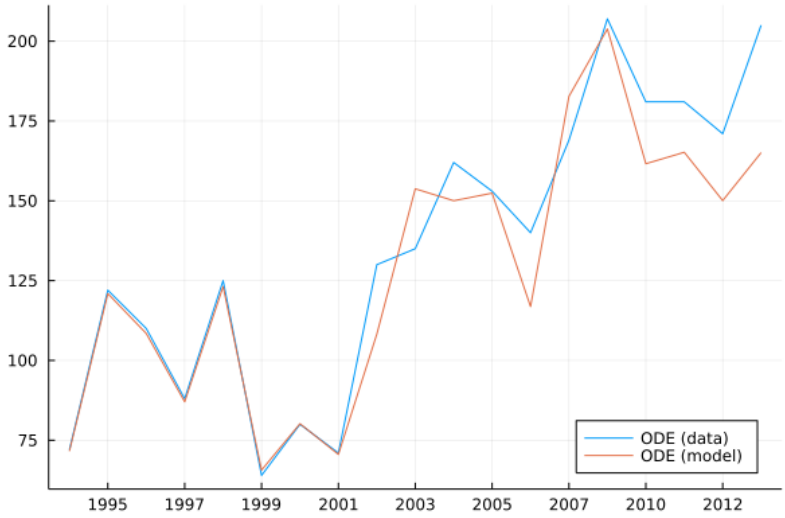
Table: Selected Estimates: "Post" Period

Program	Mean Appcost	σ Appcost	$\Sigma^{-1}\rho_{\omega_j,\varepsilon_j}$	$\Sigma^{-1}\rho_{\omega_j,s_j}$
Ode	0.382	0.0	0.362	0.717
Aar	0.137	0.285	0.537	-0.500
Cop	0.12	0.312	0.651	0.223

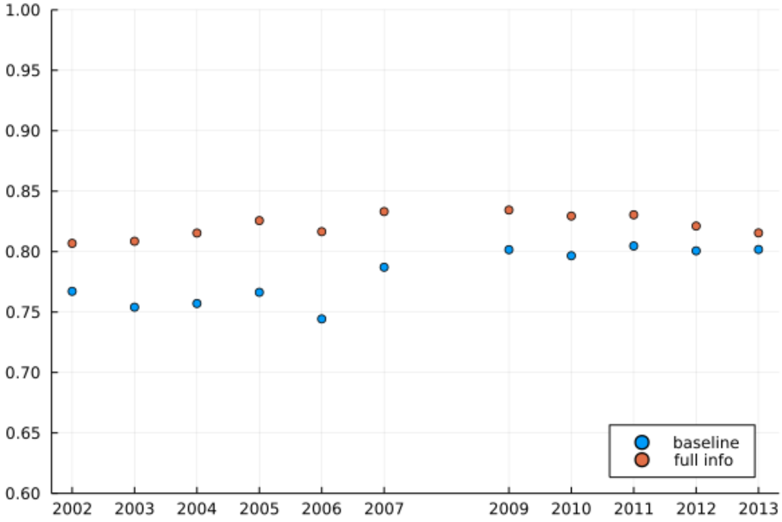
Model fit: Q1 Applications to Odense (Probit)

model	**data**	**sd (data)**	**x**
-0.258	-0.175	0.062	constant
-0.013	-0.059	0.007	GPA
0.484	0.614	0.019	aar
-0.168	-0.129	0.015	ode
-2.006	-1.933	0.16	foreign
0.273	0.274	0.017	GPAforeign

Model fit: Number of Q2 Applicants "above bar" at Odense



Perfect-Info Counterfactual: (ε, s) of each student commonly observed.



Conclusions

We document that interdependent values exist in a matching market and have real impacts on the production of doctors.

- Evidence for interdependent program values
- Student selection on preferences/talents plays important role

Next steps: implications for market design.

- Under current scheme, applicants who like program j but seem like they wouldn't are at a disadvantage, leading to inefficiency.
- Should programs be able to condition on students' rankings? Relatedly, would a multi-round (e.g. "Early Decision") decentralized process result in better matches?
- What about feasible ways for programs to share info (common exam, ...)?

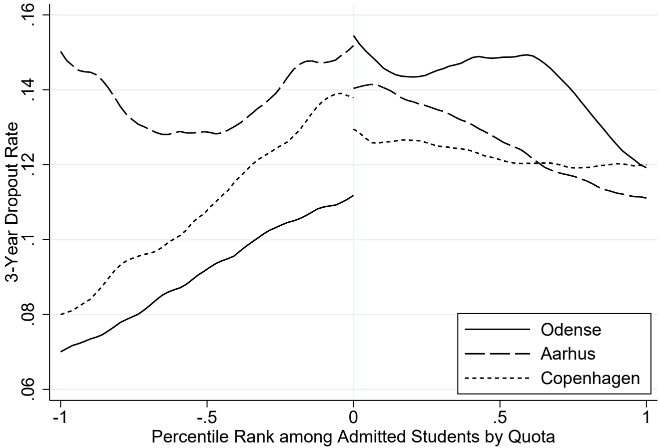
Student Preferences and Dropouts

	(1)	(2)	(3)	(4)
	3Y Dropout		Completion	
Applied Quota 2	-0.020*	-0.027**	0.023	0.035**
	(0.011)	(0.012)	(0.016)	(0.017)
Add Controls	No	Yes	No	Yes
Observations	6,607	6,607	4,694	4,694
R-squared	0.010	0.024	0.006	0.024

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

- Focus on Quota-1 admissions only to isolate self-selection of applicants
- Q2 applicants have lower dropout rates, conditional on observed characteristics (GPA, location)

Dropout rate by Q1/Q2 ranking X program



Note: Q2 admissions are ranked from -1 (highest) to 0 (lowest), Q1 admission from 0 to 1 (highest).