no strings attached

the distributional effects of unraveling in college admissions

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2025-10-29
labor lunch

This work was undertaken in the UK Office for National Statistics (ONS) Secure Research Service using data from ONS and other owners. All analysis and conclusions are those of the authors, and do not necessary reflect the view of the ONS or other data owners.

A crisis in UK college admissions

*Geoff Barton, general secretary of the Association of School and College Leaders, said: "It is **infuriating** that universities have apparently responded to calls to end the use of certain types of unconditional offers by making more of them.*

*[...] "This practice has **more to do with the frenetic scramble to put 'bums on seats' than the best interests of students**."*

*[...] Following the lifting of the cap on student numbers, there has been **fierce competition between institutions** who are dependent for their survival on undergraduate tuition fees and are recruiting from a shrinking pool of 18-year-olds.*

–The Guardian, 2018

*"We don't use them to put bums on seats, in the minister's phrase, we use them to position ourselves at the top end of the attainment range and **attract a high calibre of students** ...I want them to come here and not to a university down the road"*

–Vice-Chancellor of Sheffield Hallam Univ., 2018

*A survey of 18-year-olds by Ucas found **70% of applicants supported the use of unconditional offers**, noting: "Many speak about a reduction in **stress**, and the mental health and wellbeing benefits this confers." Applicants themselves ...welcom[e] the **certainty** of knowing they have a place...*

–The Guardian, 2019

Real markets often deviate from neoclassical, but intermediation can fail; why?

> *Unraveling is defined as future employment contracts that are signed long before employment is to begin [...] Unraveling of the appointment date is not so much about competing through strategically timing proposals and acceptances. It is more about* ***ex post inefficiencies caused by making early contracts with incomplete information.***
>
> –Li and Rosen (1996)

- Gastroenterology: –1986, 1996–2006 (Niederle and Roth, 2003)

  Offers made 1 year early, decreased mobility + scope of market
- College football bowl (post-season) games: –1992 (Fréchette et al., 2007)

  Bowls scheduled several weeks before end of regular season; coordination increased efficient matchings, viewership
- Law clerk hiring, –2017 (Avery et al., 2007)

  Hiring for clerkships began years in advance, with "exploding offers"; attempts at regulation had high non-adherence rates. New government-run online system (OSCAR) has improved coordination, match quality
- Pathology fellowships, –2025(?) (Herrmann et al., 2022)

  Offers made $\geq$2 years early; joined NMRP last year to try and fix

See also Autor (2009) for a review of intermediation in labor markets

We analyze unraveling with modern empirical methods

Previous unraveling papers examine decentralized markets, and data is often incomplete + collected via surveys

In this paper, we examine unraveling in the higher education context, studying a centralized market with early offers

Research questions

1. How did early offers affect students' match rate and quality, college graduation rates, and eventual earnings?
2. Did universities compete with each other using early offers?
3. What are the distributional effects of the ban on early offers, as measured via match results and long-term outcomes? How does this change under alternative systems (e.g., universal early offers, offers only after EOY tests)?

Today, test a model of early offers with data from the UK

Theoretical model describing early offers

- Relates to literature on unraveling (Roth and Xing, 1994; Li and Rosen, 1996; Suen, 2000; Ostrovsky and Schwarz, 2010; Saitto et al., 2024), US early decision (Avery and Levin, 2010), college app gaming + standardized tests (Lee and Suen, 2022)
- Contribution: analyze universities' decisions problem, combine with empirics

Empirical evidence testing model predictions

- Early offers given by less-selective colleges, targeting higher-ability students
- Diverts students away from selective colleges, but increased graduation rates

Describe structural model to analyze effects of early offer ban

- Connects to literature analyzing collect admissions (Kapor, 2024; Ajayi and Sidibe, 2020; Bleemer, 2024; Agarwal and Somaini, 2020)
- Contribution: link match changes to labor market outcomes

Roadmap for this talk

intro

background

model

empirics

structural

An overview of the UK college admissions system, circa 2013

Jan apply

$\sim$250K students apply to up to 5 programs (mean 4.8)

App includes GCSEs (year 11), AS-levels (year 12), personal statement, reference, A-level scores as *predicted* by teachers (year 13)

May offer

$\sim$35K programs at $\sim$160 universities make tentative offers

Acceptance conditional on A-levels (EOY tests)

App sets unobserved by unis

Jun rank

Students rank $\leq$2 offers received (mean 3.6 offers/student)

Rankings binding, all other offers forfeited

Aug accept

A-level results released, accepted to highest-ranked uni where conditions met (80% to 1st, 10% to 2nd, 10% unmatched)

Unis can still admit students who miss conditions at their discretion

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Early offers began in 2014, changing students' choice problem

Jan apply	Apply to ≤ 5 programs
May offer	Unis make ~~tentative~~ offers
Jun rank	Students rank ≤ 2 offers
Aug accept	Release test results, final match

Offers given in May now took two additional forms

Early offer — if student ranks program, **guaranteed acceptance** regardless of their A-level results

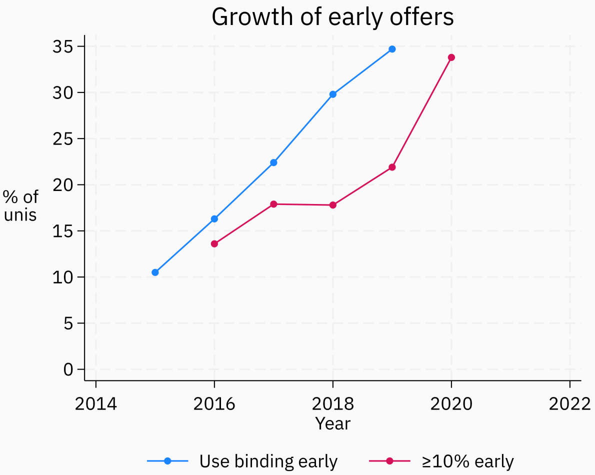
Binding early offer — like early offer, but student **must rank program first** to receive guarantee

if program ranked second, acceptance still contingent on A-level results

Akin to early action/early decision in the US context

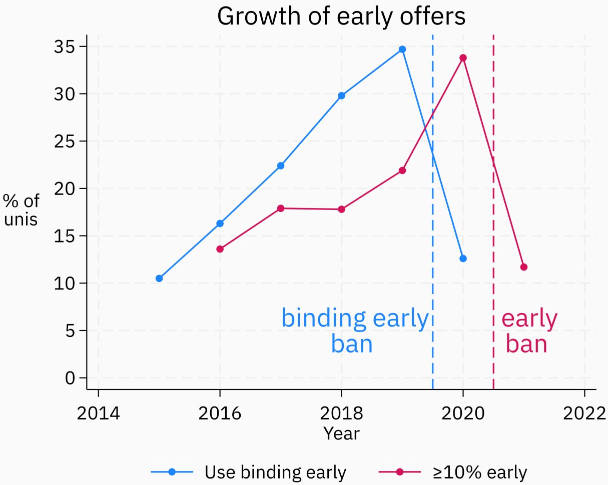
Early offers became commonplace very rapidly...

Jan apply	Apply to ≤ 5 programs
May offer	Unis make regular + early offers
Jun rank	Students rank ≤ 2 offers
Aug accept	Release test results, final match



...but not as rapidly as their fall

- 2020: UK government temporarily bans binding early offers b/c COVID-19, concerns of pressure on students
- 2021: UK unis created "Fair admissions code of practice", limiting use of early offers and binding early offers



Institutional features allow us to focus analysis on unraveling

Jan apply — Apply to ≤ 5 programs

May offer — Unis make regular + early offers

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Aug accept — Release test results, final match

- Centralized application system gives full information on the market
- Fees capped to £9,535 for domestic applicants, few price differences at uni level
- Unraveling happens on a single dimension which is observed

Rich dataset allows for more thorough investigation of unraveling

Jan apply	○	Apply to ≤ 5 programs
May offer	○	Unis make regular + early offers
Jun rank	○	Students rank ≤ 2 offers
Aug accept	○	Release test results, final match

- Applications, offers, acceptances all managed by UCAS (centralized platform)
- Data on first-time 18yo applicants from 2007–21
  more detailed data on early offers from 2013–21
- Restrict to applicants from England, Wales, Northern Ireland; Scottish EOY exams follow different timing
- Merge with data from HESA (uni enrollment, degrees), LEO (employment)

Minimal model to demonstrate key incentives behind early offers

Theoretical model demonstrates that

- Regular offers are efficient
- Early offers given by less-selective unis
- Early offers cause high-ability students with bad private signals to shift enrollment

Competition for students with identical ability signal

- 3 universities (1, 2, 3) each with capacity $\frac{1}{3}$, quality $1 \succ 2 \succ 3$
- Unit mass of students with ability $y \sim U[0,1]$ known privately
- Increasing differences in quality, ability

$$u(1;y) = y \quad u(2;y) = \frac{1}{2}y \quad u(3;y) = 0$$

- Universities' utility is average quality of enrolled students: $\int y \, \mathrm{d}y$

Design model to reflect timing of UK admissions system

$t = 0$ apply — Apply to all 3 unis

$t = 1$ offer — Unis make offers, which are regular (conditional on y) or early (accepted regardless of y)

$t = 2$ rank — Students rank all offers
If unmatched, incur cost $k = \frac{2}{5}$
Reflects uncertainty (mean-variance preferences, dislike of studying, ...)

$t = 3$ accept — Take test, revealing y
Accepted to best-ranked uni where conditions met

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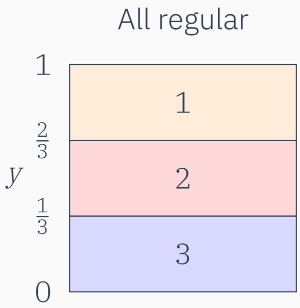
If only regular offers permitted, efficient allocation

- Consider world where early offers do not exist
- Universities make offers to all students
- Students rank $1 \succ 2 \succ 3$

Uni	Admitted students	Uni utility	Student utility
1	$y \in \left[\frac{2}{3}, 1\right]$	$\frac{5}{6}$	0.43
2	$y \in \left[\frac{1}{3}, \frac{2}{3}\right]$	$\frac{1}{2}$	−0.15
3	$y \in \left[0, \frac{1}{3}\right]$	$\frac{1}{6}$	−0.40

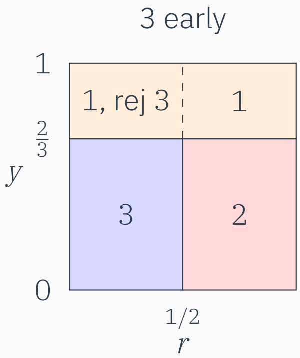


- Under any matching, total uni utility constant at $\frac{1}{2}$
- Student ex-ante utility is $\frac{13}{36} = 0.3611$

From regular offer status quo, university 3 has incentive to make early offers

- Unis can now make early offers, where student guaranteed acceptance; must rank first at $t = 2$, else forfeited
- Uni 3 gives early offers to half of all students, who take offer if $y \leq \frac{2}{3}$

Uni	Admitted students	Uni utility	Student utility
1	$y \in \left[\frac{2}{3}, 1\right]$	$\frac{5}{6}$	0.43
2	$y \in \left[0, \frac{2}{3}\right], r \geq \frac{1}{2}$	$\frac{1}{3}$	-0.23
3	$y \in \left[0, \frac{2}{3}\right], r \leq \frac{1}{2}$	$\frac{1}{3}$	0



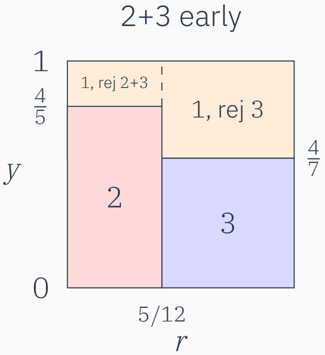
- Intuition: 3 “poaches” students admitted to 2 who have weakest for 2, increasing average ability at 3

In response, university 2 also makes early offers

- A student accepts early from 2 if $y \leq 0.8$
- A student accepts early from 3 if wouldn't meet 1's conditions
- Market clearing implies 2 makes early offers to $\frac{5}{12}$ of students, 3 to all

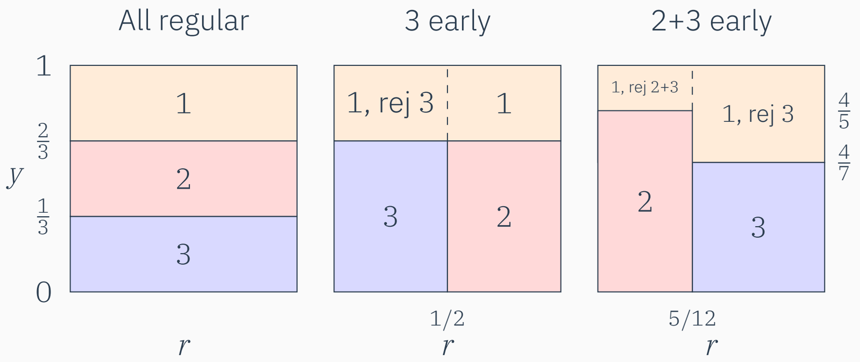
Uni	Admitted students	Uni u	Student u
1	$y \geq \frac{4}{5}$ or $\left(y \geq \frac{4}{7}, r \geq \frac{5}{12}\right)$	0.81	0.41
2	$y \leq \frac{4}{5}, r \leq \frac{5}{12}$	0.40	0.20
3	$y \leq \frac{4}{7}, r \geq \frac{5}{12}$	0.29	0

- Intuition: less adverse selection from early offers because of 3's offers, so 2 can also make early offers profitably

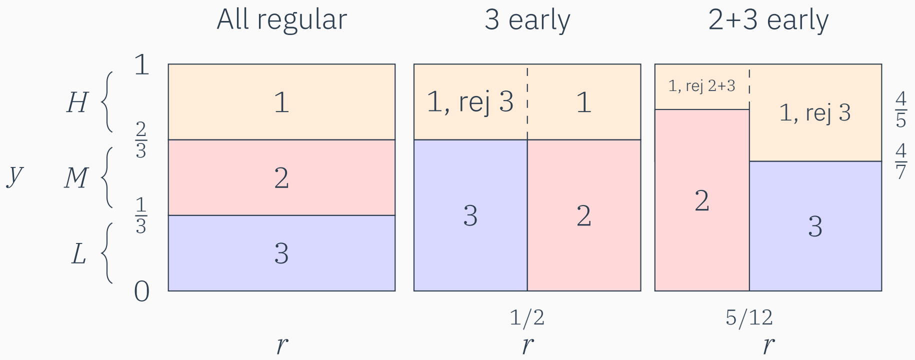


Market partially unravels from 3 to 2, but not fully

- Uni 1 still makes only regular offers; adverse selection from early offers too strong
- Uni 2 does not make early offers if 3 doesn't; if they did, more students join from $[0, \frac{1}{3}]$ than from $[\frac{2}{3}, 1]$ (specifically, $y \leq 2k = 0.8$), decreasing utility



Shifts across universities lead to increase in welfare, decrease in match quality



Uni u (1, 2, 3)	$(0.83, 0.50, 0.17)$	$(0.83, 0.33, 0.33)$	$(0.81, 0.40, 0.29)$
Stu u (H, M, L)	$(0.43, -.15, -.40)$	$(0.43, -.08, -.16)$	$(0.44, 0.14, 0.07)$
Stu u (w/ test)	-0.039	0.067	0.205
Stu u (match only)	0.361	0.333	0.338

Model generates three testable predictions

1. Universities with *ex ante* lower student quality more likely to give early offers due to adverse selection
2. Early offers targeted towards high-ability students, accepted by students with low private signal

   Former not shown in slides; intuitively, if 2 has a signal of $y \lessgtr 0.5$, then will target early offers to $y \geq 0.5$ details
3. High-ability students divert away from most competitive universities, decreasing match quality

Evidence on prediction 1: who gives early offers

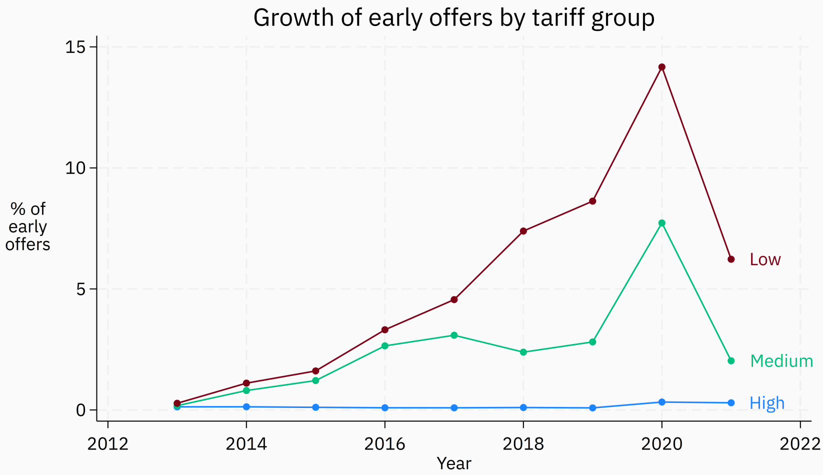
1. **Universities with *ex ante* lower student quality more likely to give early offers due to adverse selection**
2. Early offers targeted towards high-ability students, accepted by students with low private signal
3. High-ability students divert away from most competitive universities, decreasing match quality

Additionally, show evidence on long-term effects of early offers

Early offers driven by low, medium tariff universities

Graph percentage of offers that are early for unis in each tariff group (roughly, quality tercile)

binding early



Early offers given by less-selective, less-popular courses

	(1) Frac. early offers	(2) Use early offers
Avg. GCSE ptile, 2012 admit class	-0.0421**	-0.284***
	(0.0179)	(0.00821)
Avg. A-level ptile	-0.127***	0.0292
	(0.0173)	(0.00883)
Yield rate, 1st (lowest) quintile	0.0420***	0.0944***
	(0.00481)	(0.0148)
2nd quintile	0.0472***	0.132***
	(0.00539)	(0.00272)
3rd quintile	0.0369***	0.0901***
	(0.00371)	(0.0130)
4th quintile	0.0194***	0.0553***
	(0.00334)	(0.0124)
Observations	16,115	16,115

Regress fraction of early offers on course characteristics using 2012 data

Sample includes all courses from 2013 to 2021 in the 20 most popular majors. Include year, major, tariff group FEs

Evidence on prediction 2: who gets/takes early offers

1. Universities with *ex ante* lower student quality more likely to give early offers due to adverse selection
2. **Early offers targeted towards high-ability students, accepted by students with low private signal**
3. High-ability students divert away from most competitive universities, decreasing match quality

Additionally, show evidence on long-term effects of early offers

Ability is the strongest predictor of early offers

	(1) Got early	(2) Got binding early	(3) Got any early
A-level pred, 5th (highest) quintile	0.0794***	0.185***	0.246***
	(0.00107)	(0.00142)	(0.00170)
4th quintile	0.0836***	0.146***	0.214***
	(0.00107)	(0.00132)	(0.00161)
3rd quintile	0.0551***	0.104***	0.144***
	(0.000880)	(0.00100)	(0.00126)
2nd quintile	0.0364***	0.0570***	0.0904***
	(0.000749)	(0.000780)	(0.00103)
Constant	0.0135***	−0.0206***	−0.00647***
	(0.00121)	(0.00130)	(0.00167)
N	1,215,325	1,215,325	1,215,325
Mean	0.0588	0.1213	0.1995
r^2 (adj.)	0.0775	0.134	0.183
F	2016.1	6044.8	9461.3

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regress indicator for receiving an offer type on quintile of GCSEs (math and english) and predicted A-levels.

Regressions include FEs for year and SES quintile

more means

Conditional on ability, students taking early offers achieve lower

	(1) A-level percentile	(2) Underachieved A-levels
Rank early (any) 1st	−0.0485***	0.0818***
	(0.000874)	(0.00205)
Got early	0.0252***	−0.0241***
	(0.000874)	(0.00214)
Got binding early	0.0112***	−0.0135***
	(0.000644)	(0.00160)
N	1,213,623	1,213,623
Mean	0.4569	0.6970
r^2 (adj.)	0.660	0.157
F	22763.6	5387.6

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regress A-level performance on indicators for receiving/ranking early offer.

Two potential explanations

- Adverse selection (model prediction): takers have low private signal
- Moral hazard: early offers reduce A-level effort

Regressions include FEs for year, SES, ability, major, number of courses ranked, and applications sets/offers (grouped at the tariff level)

more

Evidence on prediction 3: match effects

1. Universities with *ex ante* lower student quality more likely to give early offers due to adverse selection
2. Early offers targeted towards high-ability students, accepted by students with low private signal
3. **High-ability students divert away from most competitive universities, decreasing match quality**

Additionally, show evidence on long-term effects of early offers

Students are more likely to rank early offers first

	(1) Choose as 1st	(2) Choose as 2nd	(3) Decline
Is early offer	**0.189***** (0.004)	**-0.027***** (0.003)	**-0.162***** (0.003)
2nd highest avg. income of offers	-0.078*** (0.003)	0.071*** (0.002)	0.007*** (0.002)
3rd+ highest avg. income of offers	-0.155*** (0.003)	0.109*** (0.002)	0.045*** (0.002)
Observations	1,013,741	1,013,741	1,013,741

Standard errors in parentheses. Include course, year FE, # of Us+CUs. Restrict to students w/ $\geq$ 3 offers.

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Regress student offer response (2013–21) on offer type, exposure to U/CU offers, and rank of uni in offer set

Rank determined by average post-course earnings of students in 2011

The "early offer" boost overcomes students' distaste for lower-ranked colleges

	(1) Choose as 1st	(2) Choose as 2nd	(3) Decline
Is early offer	0.189***	-0.027***	-0.162***
	(0.004)	(0.003)	(0.003)
2nd highest avg. income of offers	-0.078***	0.071***	0.007***
	(0.003)	(0.002)	(0.002)
3rd+ highest avg. income of offers	-0.155***	0.109***	0.045***
	(0.003)	(0.002)	(0.002)
Observations	1,013,741	1,013,741	1,013,741

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Regress student offer response (2013–21) on offer type, exposure to U/CU offers, and rank of uni in offer set

Rank determined by average post-course earnings of students in 2011

Students of same ability go to lower-ranked unis when early offer taken

Regression includes FEs for year, SES, ability, major, and application sets/offers.

	(1) Enrolled (Russell)	(2) Enrolled (Oxbridge)	(3) Enrolled (High Tariff)	(4) Enrolled (Med. Tariff)	(5) Enrolled (Low Tariff)
Rank early (any) 1st	−0.0956***	−0.0180***	−0.0767***	0.0884***	0.0352***
	(0.00150)	(0.000470)	(0.00137)	(0.00197)	(0.00171)
Got early	0.0346***	0.0100***	0.0457***	−0.0243***	−0.0065***
	(0.00152)	(0.000409)	(0.00144)	(0.00203)	(0.00190)
Got binding early	0.0195***	0.00220***	0.0456***	−0.0184***	−0.0179***
	(0.00134)	(0.000577)	(0.00121)	(0.00146)	(0.00122)
N	1,213,623	1,213,623	1,213,623	1,213,623	1,213,623
Mean	0.2909	0.0196	0.3189	0.2900	0.2664
r^2 (adj.)	0.426	0.185	0.552	0.333	0.467
F	1581.2	732.6	1423.6	626.9	1061.3

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Unis who give early offers increase in popularity+HS grades, but A-levels drop

	(1) Frac. early offers	(2) Use early offers
Avg. GCSE ptile	.0596***	.0842
	(.0176)	(.0590)
Avg. A-level ptile	-.164***	-.302***
	(.0168)	(.0502)
Yield rate, 1st (lowest) quintile	-.0852***	-.148***
	(0.00627)	(.0179)
2nd quintile	-.0575***	-.110***
	(0.00564)	(.0168)
3rd quintile	-.0339***	-.0702***
	(0.00516)	(.0160)
4th quintile	-.0231***	-.0530***
	(0.00421)	(.0140)
Observations	16,115	16,115

Regress fraction of early offers on course characteristics of that year's admitted class

Sample includes all courses from 2013 to 2021 in the 20 most popular majors. Include year, major, tariff group FEs, and controls for 2012 admit class characteristics, quintile of yield rate in 2012.

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Beyond the model: evidence on students' long-term outcomes

1. Universities with *ex ante* lower student quality more likely to give early offers due to adverse selection
2. Early offers targeted towards high-ability students, accepted by students with low private signal
3. High-ability students divert away from most competitive universities, decreasing match quality

Additionally, show evidence on long-term effects of early offers

Students who rank early offers (conditional on receipt) attend uni more

	(1) Enrolled (main)	(2) Enrolled (cycle)	(3) Enrolled (ever)
Rank early (any) 1st	0.114***	0.0468***	0.0253***
	(0.00156)	(0.00119)	(0.000931)
Got early	0.00919***	0.0150***	0.00604***
	(0.00165)	(0.00131)	(0.00110)
Got binding early	0.00992***	0.00939***	0.00168*
	(0.00132)	(0.000972)	(0.000732)
N	1,213,623	1,213,623	1,213,623
Mean	0.7567	0.8753	0.9460
r^2 (adj.)	0.272	0.243	0.155
F	19772.9	3143.3	920.4

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regress enrollment in university on indicators for receiving/ranking early offer.

51K students got early offer in 2019, didn't rank it first; if they did, then $\sim$5,800 more students would enroll from main match (2,400 that cycle, 1,300 ever)

Regressions include FEs for year, SES, ability, major, number of courses ranked, and applications sets/offers (grouped at the tariff level)

Gap in degree attainment falls to near 0 over time

	(1) Degree in $\leq$ 3 years	(2) Degree in $\leq$ 4 years	(3) Degree in $\leq$ 5 years	(4) Degree in $\leq$ 6 years
Rank early (any) 1st	0.0621***	0.0487***	0.0209***	0.0134
	(0.00345)	(0.00431)	(0.00542)	(0.00845)
Got early	0.00892**	0.0235***	0.0134*	0.0163
	(0.00336)	(0.00418)	(0.00566)	(0.00850)
Got binding early	0.0175***	0.0271***	0.0221***	0.0204**
	(0.00257)	(0.00313)	(0.00382)	(0.00631)
N	802,330	637,320	469,630	304,060
Mean	0.3873	0.6510	0.7355	0.7623

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regress degree attainment on indicators for receiving/ranking early offer.

Regressions include FEs for year, SES, ability, major, number of courses ranked, and applications sets/offers (grouped at the tariff level)

Affects downstream earnings, though estimates imprecise

	(1) Earnings at 22	(2) Earnings at 25	(3) Earnings at 27 (pred.)
Rank early (any) 1st	195.2*	381.8	−329.3***
	(84.80)	(1051.2)	(36.28)
Got early	−103.7	−1117.8	−18.74
	(80.76)	(812.8)	(35.55)
Got binding early	−58.69	0	−1.642
	(67.73)	(.)	(28.64)
N	547,020	130,070	792,920
Mean	1.3e+04	2.4e+04	2.8e+04

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regress earnings (observed for 22, 25, predicted for 27) on indicators for receiving/ranking early offer.

Regressions include FEs for year, SES, ability, major, number of courses ranked, and applications sets/offers (grouped at the tariff level)

Estimating general equilibrium effects

- Taking an early offer leads to higher uni enrollment rate, but at lower-ranked universities
- May have effects on students who don't get early offers if, for example, fewer low-ability students now get regular offers
- A regression to run...

$$Y_{it} = \alpha_{a(i)} + \gamma_t + \sum_k \beta_k \mathbf{1}\{K_{it} = k\} + X_{it}\delta + \varepsilon_{it}$$

where K_{it} is the number of years since the introduction of early offers for students' application set $a(i)$

Use rich choice data to understand net effects of early offer ban

- When early offers were banned in 2020/2021, how did students' match outcomes change? How did this impact their degree attainment, graduation timeline, and eventual labor-market outcomes?
- What would happen in a system with offers only given out after A-level results? Or where A-level results considered by no uni (i.e., all early offers)? Or with a full centralized match?

Features of setting enable analysis via a structural model

$t = 0$ apply	Apply to ≤5 programs
$t = 1$ offer	Unis make regular + early offers
$t = 2$ rank	Students rank ≤2 offers
$t = 3$ accept	Release test results, final match

- Observed initial choice sets, offers, final rankings, enrollment
- Full student-level covariates (demographics, test scores, ...)
- Offer shifter: time-varying exposure to early offers, as students have no knowledge of who gives/receives early offers
- App shifter: distance to university (affecting students only); standard in literature

more

This project: understanding unraveling through UK college admissions

- Analyze unraveling in the UK college admissions market, where early offers change matching
- Derive and test three predictions from a theoretical model
  - Less-selective universities give early offers
  - Early offers go to high-ability students, who take it if low private signal
  - This leads to changes in match quality for both sides of the market
- Structural model to analyze welfare impacts of early offer ban, counterfactual systems (results to come!)

questions or comments? padajar@mit.edu

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Model centered on students' risk, universities' desire for high-ability students

$t = 0$ apply — Apply to ≤5 programs

$t = 1$ offer — Unis make regular + early offers

$t = 2$ rank — Students rank ≤2 offers

$t = 3$ accept — Release test results, final match

0. Students choose application set A_i
1. Unis admit B_s, but uncertain of student ability
2. Students rank offers received, with additional preference shock
3. Students accepted to highest-ranked uni where they meet conditions (if applicable)

Structural model based on Kapor (2024), augmented to account for early offers

Work backwards from $t = 3$ to describe model back

Students with regular offers admitted if exceed relevant conditions

$t = 0$ apply		Apply to $\leq$5 programs
$t = 1$ offer		Unis make regular + early offers
$t = 2$ rank		Students rank $\leq$2 offers
$t = 3$ accept		Release test results, final match

0. Students choose application set A_i
1. Unis admit B_s, but uncertain of student ability
2. Students rank offers received, with additional preference shock
3. **Students accepted to highest-ranked uni where they meet conditions (if applicable)**

   Student i receives test score r_i
   For regular offers, pass s's conditions if

$$r_i \geq \underline{r}_s$$

   No conditions for early offers

Students rank offers received, accounting for risk

$t = 0$ apply		Apply to $\leq$5 programs
$t = 1$ offer		Unis make regular + early offers
$t = 2$ rank		Students rank $\leq$2 offers
$t = 3$ accept		Release test results, final match

0. Students choose application set A_i
1. Unis admit B_s, but uncertain of student ability
2. **Students rank offers received, with additional preference shock**

   Utility for i at s now

   $$u_{is} = \underbrace{U_{is}}_{\text{ex-ante utility}} + \underbrace{\varepsilon_{is}^{\text{enroll}}}_{\text{logit shock}}$$

   Incur cost if not matched with certainty; rank unis to maximize utility given beliefs about ability, acceptance odds detail
3. Students accepted to highest-ranked uni where they meet conditions (if applicable)

Students rank offers received, accounting for risk

$t = 0$ apply	○	Apply to $\leq$5 programs
$t = 1$ offer	●	Unis make regular + early offers
$t = 2$ rank	○	Students rank $\leq$2 offers
$t = 3$ accept	○	Release test results, final match

0. Students choose application set A_i
1. **Unis admit B_s, but uncertain of student ability**

   Uni's utility over students includes observable characteristics, unobserved characteristics (e.g., essays), unknown ability (A-level tests)

   Admit students up to capacity using a cutoff rule; early offers impact likelihood of enrollment

   detail
2. Students rank offers received, with additional preference shock
3. Students accepted to highest-ranked uni where they meet conditions (if applicable)

Students rank offers received, accounting for risk

$t = 0$ apply — Apply to $\leq$5 programs

$t = 1$ offer — Unis make regular + early offers

$t = 2$ rank — Students rank $\leq$2 offers

$t = 3$ accept — Release test results, final match

0. **Students choose application set A_i**

   Students have utility with school-specific quality, random coefficients over school characteristics, course-specific shock

   Choose application set to maximize expected utility, given private ability signals detail

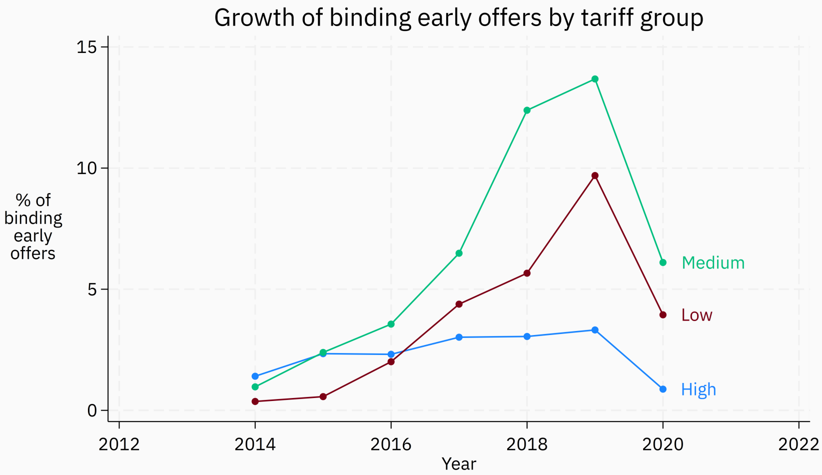
1. Unis admit B_s, but uncertain of student ability
2. Students rank offers received, with additional preference shock
3. Students accepted to highest-ranked uni where they meet conditions (if applicable)

Computational procedure for estimation

$t = 0$ apply	Apply to $\leq$5 programs
$t = 1$ offer	Unis make regular + early offers
$t = 2$ rank	Students rank $\leq$2 offers
$t = 3$ accept	Release test results, final match

- Initial estimates on single major, or single set of related majors (i.e., business + management)
- Aggregate courses by major $\times$ tariff group, allowing students to apply to a tariff group multiple times
- Use GMM to maximize the likelihood of observed application sets ($t = 0$), admissions decisions ($t = 1$), and rankings ($t = 2$)
- Estimate per-course effects on outcomes, including wages, college graduation
- Using parameter estimates, simulate match under counterfactual policies (all early offers, offers only after after A-level results) back

Binding early offers driven by medium tariff universities



◂ back

Ability is the strongest predictor of early offers

	(1) Binding early offer	(2) Early offer
Low-SES neighborhood	-0.002***	0.000
	(0.000)	(0.000)
Female	0.009***	0.003***
	(0.001)	(0.000)
GCSE core ptile	**0.154*** **	**0.052*** **
	(0.007)	(0.003)
A-level pctile (achieved)	**0.181*** **	**0.070*** **
	(0.006)	(0.003)
Observations	1,913,966	1,913,966
R-squared	0.293	0.289

Regress offer type on student characteristics

Restricted to offers in 2014–19 from courses that ever give >10% U-offers. SEs clustered at course level. All regressions include FEs for year, course, school, race indicators, and disability indicators.

back

High-SES, higher-achieving students receive more U/CU

Table shows mean applicant characteristics for courses, split by offer type.[1]

back

	Receive CU		Receive U		Receive C	
	Mean	N	Mean	N	Mean	N
Low-SES neighborhood	**0.27**	229,089	**0.35**	110,141	**0.34**	1,902,831
Female	0.60	229,285	0.60	110,254	0.55	1,904,804
Low-SES parent occ.	**0.19**	229,285	**0.24**	110,254	**0.22**	1,904,804
White	0.77	229,285	0.80	110,254	0.75	1,904,804
Black	0.05	229,285	0.05	110,254	0.06	1,904,804
Disabled	0.09	229,285	0.10	110,254	0.08	1,904,804
Only A-level tests	0.89	194,230	0.82	81,451	0.86	1,593,058
Only BTEC tests	0.13	222,549	0.22	104,283	0.14	1,842,258
GCSE core ptile	0.55	228,276	0.45	109,535	0.45	1,890,153
Alevels/BTEC ptile	**0.56**	217,589	**0.49**	100,236	**0.42**	1,791,337

[1] IMD is the SES quintile, 1 the lowest.

Admitted classes have higher predicted scores, lower achieved scores

	(1) A-level pctile (pred.)	(2) A-level pctile (act.)
0% - 10%	0.00149	-0.00697***
	(0.00135)	(0.00133)
10% - 25%	**0.0111*** **	**-0.00646*** **
	(0.00181)	(0.00179)
25% - 50%	**0.0136*** **	**-0.0113*** **
	(0.00207)	(0.00198)
50% - 75%	**0.0157*** **	**-0.0162*** **
	(0.00279)	(0.00274)
75% - 100%	**0.00771* **	**-0.0228*** **
	(0.00391)	(0.00393)
Constant	0.465***	0.495***
	(0.000481)	(0.000461)
Observations	65,499	65,718
Sample Mean	0.468	0.492
Sample SD	0.184	0.190

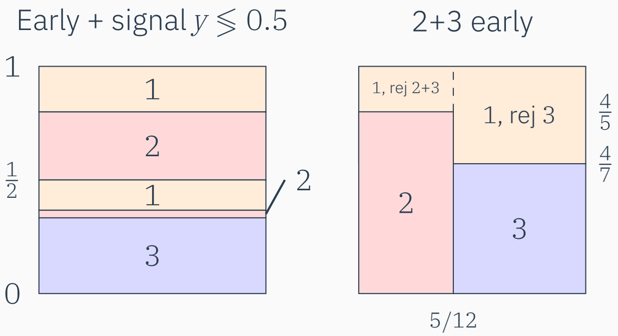
Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Regress academic characteristics of enrolled students on bins of rate of early offers

Regression includes course, year FEs. Baseline is 0% U-offer.

back

Graphical proof of targeting to ability



With a coarse signal of ability, 2 can target early offers to $y > 0.5$; $y \in [0.5, 0.8]$ take offer

2 also give regular offers to small segment of lower signal

Note: Not an equilibrium, as 1 now has incentive to make early offers to $y > 0.5$, all of whom take it

back

Model works backwards from students' final rankings

Let student i's utility for course s (including outside option 0) after receiving offers be

$$u_{is} = U_{is} + \varepsilon_{is}^{\text{enroll}}$$

where

U_{is}	i's ex-ante utility for s (i.e., before receiving offers)
$\varepsilon_{is}^{\text{enroll}}$	a nested logit shock with parameter λ comparing outside option (0) and "inside" options (courses where i admitted)

Students then rank offers to maximize utility

Following Agarwal and Somaini (2018), let students have (accurate) beliefs L_{R_i} about admissions to each course if they submit ranklist R_i

Incur cost $c_i^{\text{test}} = \gamma_z^{\text{test}} z_i^{\text{prefs}}$ when studying EOY exams, 0 if exams not required, where z_i^{prefs} is a vector of student characteristics impacting preferences

Students choose ranklist R_i to maximize expected utility; implies MLE estimator

$$\hat{\theta} = \arg\max_{\theta} \sum_{i=1}^{N} \log \mathbb{P}\left[R_i = \arg\max_{R_i} u_{is} L_{R_i} - \gamma_z^{\text{test}} z_i \middle| z_i; \theta \right]$$

◂ back

Course give offers to their cohort of most-preferred students

Course j's utility for student i is

$$\pi_{is} = z_i^{\text{admit}} \gamma^{\text{admit}} + q_i + r_i + \mu_{is}^{\text{admit}}$$

z_i^{admit}	vector of student characteristics used for admission (predicted A-levels, GCSEs, SES)
q_i	ability parameter commonly observed by all courses (i.e., teacher recs, extenuating circumstances), $\sim N\left(0, \sigma_q^2\left(z_i^{\text{info}}\right)\right)$
r_i	ability parameter observed via EOY test, $\sim N\left(0, \sigma_r^2\left(z_i^{\text{info}}\right)\right)$
s_i^q, s_i^r	signals observed by students; jointly normal with q_i, r_i, respectively
μ_{is}^{admit}	iid $N(0,1)$ course-specific shock to s of admitting i, observed only by courses

Courses set cutoffs to maximize expected utility given expected enrollment

Course s gives C offer (resp. U offer) if $\pi_{is} \geq \underline{\pi}_s^C$ (resp. $\pi_{is} \geq \underline{\pi}_s^U$). C offers come with additional threshold $\underline{r}_s^C$ which must be met to be admitted

Course s believes student of type z_i^{admit}, q_i with a C offer will attend with probability

$$\mathbb{P}\left[i \text{ attends } s \mid U\right] = \left(1 + \exp\left(\beta_s^{z,U} z_i^{\text{admit}} + \beta_s^{q,U} q_i\right)\right)^{-1}$$

From this, unis back out per-year aggregate "outside option" utility for each student type (treating true student utility for s as comparison as known)[2]

Use years with C and U offers to estimate "value" of a U offer, from s's perspective

Correlation in offers gives q, while differences in offers gives uni parameters; use distance to universities as shifter of applications back

[2] This is done because courses are unaware of a students' exact application portfolio.

Students have ex-ante utility over courses

Let student ex-ante utility for course s be

$$U_{is} = \delta_s + w_s \beta_i^w + x_{is} \beta_i^x + z_{is}^{\text{admit}} \beta_i^z + \nu_{is}^{\text{admit}}$$

δ_s	school-specific quality term
w_s	vector of school characteristics, with random coefficients $\beta_i^w \sim N(0, \sigma^w)$
x_{is}	preference shifters (distance to college, indicator for nearby college, Russell Group$\times z_i^{\text{admit}}$)
z_{is}^{admit}	vector of student characteristics used for admission (predicted A-levels, GCSEs, SES)
ν_{is}^{admit}	iid $N(0, \sigma_s^2)$ course-specific shock, $\perp z_i, x_{is}$

Students then choose portfolio given expected utilities

Expected value of portfolio A is

$$V_i(A) = \sum_{B \subseteq A} P_i(B; A) \log\left(1 + (\mathbb{E}U(B)/\lambda)^{\lambda}\right)$$

where $P_i(B; A)$ gives the probability of being admitted to only the subset $B \subseteq A$.[3]

Students choose an application portfolio A to maximize $V_i(A) - C(|A|)$, where C is a cost function for the size of the application portfolio

Initial + final choices, differences between cohorts subject to unconditional offers, pins down preferences ◂ back

[3] Kapor(2024) provides a way to compute these probabilities quickly, using only $P(B; B)$ for every subset $B \subseteq A$.