Getting In and Getting Through: Ex Ante Beliefs and Counterfactual Outcomes in Centralized College Admissions*

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Abstract

College applicants in centralized systems rank programs before they know where they will be admitted and whether they will enroll and complete. We surveyed Norwegian applicants about these prospects for their first two choices after applying but before admissions and link their beliefs to administrative records. Comparing applicants just above and below admission cutoffs allows us to validate these beliefs with outcomes. Marginal applicants slightly overpredict enrollment if admitted to their first choice and underpredict it at their second, increasing between-program prediction error. While they substantially overpredict completion given enrollment for both programs, the error in the difference between programs is much smaller. In a model of applicants' rankings, correcting completion beliefs for one program changes the predicted probability of ranking the current first choice above the second by 12–14 percentage points, whereas correcting both barely changes it. Our study sheds light on validation of subjective counterfactuals and implications of their correction.

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1 Introduction

Centralized admissions systems allocate scarce seats in higher education for millions of applicants worldwide, based on student preferences, institutional priorities, ranking criteria, seat capacities, and the matching algorithm used by the clearinghouse. Typically, students submit their preferences by listing and rank-ordering their preferred programs. Submitted rankings are a major determinant of the resulting allocations and are especially consequential for applicants on the margin between a higher- and a lower-ranked program. The stakes of these applications can be very high (Kirkebøen et al., 2016).[1]

To rank one program above another, applicants must form accurate beliefs about what admission to each program would result in, making downstream outcomes such as enrollment and completion ("getting through") as relevant as admission itself ("getting in") (Gandil, 2025; Gandil and Leuven, 2025).[2]

Forming accurate beliefs can be informationally demanding for applicants, who need to evaluate for multiple programs – and compare across programs – the likelihoods of at least three linked stages: (i) receiving an offer, (ii) enrolling if offered, and (iii) completing if enrolled. Forecast errors at any stage can be consequential. They can distort submitted rankings and application portfolios (e.g., Agte et al. 2024; Larroucau et al. 2025), affect how applicants and policymakers evaluate capacity expansions at oversubscribed programs (e.g., Tincani et al., 2025), and change the conclusion of welfare comparisons between alternative assignment mechanisms (e.g., Kapor et al. (2020)).

This paper studies applicants' beliefs about their first, second, and first-versus-second choice over the offer-enrollment-completion pipeline; how their subjective counterfactuals compare with objective ones at the admissions margin; where forecast errors enter; and the resulting implications for application rankings.

Subjective counterfactuals are central to most economic models and analysis, but assessing their accuracy is challenging. It requires credibly identifying relevant counterfactual outcomes in a well-defined population after measuring corresponding subjective counterfactuals in the same population. However, while we observe what happens along the chosen path, we never observe what would have happened under the best alternative.[3]

Our paper addresses this challenge in the context of Norwegian higher education, where admission to oversubscribed programs is based on score cutoffs unknown to ap-

[1] Kirkebøen et al. (2016) estimate that in Norway (the context of our study) the earnings payoff to one's preferred field over the next best rivals the college wage premium for many fields.

[2] Depending on the incentive properties of the matching algorithm – and on their understanding by applicants – submitted rankings need not depend on assignment chances. At the same time, accurate beliefs about assignment chances can aid program search and application portfolios (Arteaga et al., 2022).

[3] On the other hand, assessing the accuracy of beliefs or expectations about "simple" variables against their realizations has a longstanding tradition within rational expectations tests (e.g., Muth, 1961; Lovell, 1986; Pesaran and Weale, 2006; D'Haultfoeuille et al., 2021; Crossley et al., 2024).

plicants, yielding a fuzzy regression discontinuity design for local identification of causal effects of program admission (Kirkebøen et al., 2016). The Norwegian setting enables us to combine three ingredients hardly available together. First, a large, post-application, and pre-admission survey of about 9,000 applicants, eliciting their subjective expectations about admission, enrollment if admitted, and completion if enrolled, for their first- and second-ranked programs. Second, survey-linked administrative records on the same outcomes. Third, the fuzzy regression discontinuity design provided by the centralized admissions system, which enables us to compare subjective and objective counterfactuals for first- and second-best programs among applicants who just made or just missed their first choice. The paper's main contribution is therefore to bring prospective, state-contingent beliefs linked to administrative records and design-based identification together at scale.[4]

We find that, on average, marginal applicants make relatively small errors in predicting enrollment and pretty large ones in predicting completion. In particular, these applicants report probabilistic beliefs of enrolling if admitted that are close to the design-based estimates; whereas they substantially overestimate their likelihood of completing if admitted to either program (0.77 vs 0.44 for the first choice; 0.53 vs 0.30 for the second).[5]

At the same time, those applicants make opposite-sign prediction errors for first- and second-choice enrollment and same-sign errors for completion. This results in a substantial 14-percentage-point overestimation of the first- versus second-choice enrollment advantage, but a smaller, statistically insignificant overestimation of the completion advantage (0.10, SE 0.08).

Before admission, applicants mainly overpredict whether they will finish a program if they enroll. We show this by splitting the forecast errors for each program into the parts that arise at each stage: admission (admission realization component), take-up after admission (personal component), and completion after enrollment (persistence component). Mean stated admission probabilities exceed realized admission rates by 12 percentage points for the first choice and 16 for the fallback choice. Mean take-up errors are modest for both programs. Persistence overprediction is substantial for both programs, among marginal and all admitted applicants, and in every subgroup we examine.[6]

Where errors appear to arise also depends on how a forecast is conditioned. Among marginal applicants, realized second-choice enrollment far exceeds the forecast mainly

[4] Joint measurement of subjective and objective returns to admission is central. Within a formal model of school-work decisions and wage outcomes, Manski (1993) shows that understanding how decision makers' perceived returns to schooling relate to objective returns is essential for interpreting educational choices and for econometric inference on objective returns and other equilibrium outcomes in models with selection.

[5] Completion overprediction is consistent with US evidence on educational expectations by Fischhoff et al. (2000), Cowan (2018), Stinebrickner and Stinebrickner (2012, 2014a), and Giustinelli (2023)'s review.

[6] Analyses that isolate sources of belief errors when predicting sequential or joint outcomes in other settings include Gong et al. (2019), Crossley et al. (2022), Gong et al. (2022), and Caplin et al. (2025).

because the forecast allows for not receiving a second-choice offer. The gap is much smaller when beliefs are conditioned on not being admitted to the first choice.

How do these forecast errors matter for applicants' rankings? Correcting persistence beliefs for one program shifts rankings much more than correcting them for both. We estimate a choice model for applicants' ordering of their first two programs and predict how rankings change when take-up and persistence beliefs are corrected for one program or both, holding the admissions environment fixed. Among marginal applicants, correcting persistence beliefs for only one program makes the other program look relatively better, changing the probability of ranking the current first choice above the second by 12–14 percentage points. Correcting persistence beliefs for both programs has almost no effect. Correcting take-up beliefs for both, or both stages together, lowers this probability modestly (by 3–5 points). Among all applicants, correcting persistence beliefs for one program also shifts rankings more than correcting both.

Taken together, these results show that inaccurate beliefs about each program do not imply inaccurate beliefs about how programs compare. Applicants rank programs by comparing them. Small errors at each program in opposite directions can therefore add up, while large errors in the same direction can cancel. This matters both when we assess beliefs and when we try to correct them. Correcting completion beliefs for only one program, for example, can create an error in the comparison where there was little before. To learn whether belief errors affect choices, we therefore need to compare beliefs with outcomes at the stages that enter these choices and for the alternatives being compared.

Methodologically, we build on and extend the literature that uses survey expectations to measure subjective counterfactuals and their contrasts, including the perceived returns to schooling (e.g., Dominitz and Manski, 1996; Arcidiacono et al., 2020; Wiswall and Zafar, 2021; Angelov et al., 2026) and other perceived effects (e.g., Hudomiet et al., 2021; Giustinelli and Shapiro, 2024; Briggs et al., 2024; Meango and Girsberger, 2026).[7]

Assessing the accuracy of those kinds of beliefs requires comparing them with the corresponding outcomes at each stage, for each alternative, and under the same conditions. Two recent studies also combine state-contingent beliefs with research designs that allow such comparisons in other settings: Briggs et al. (2024) study the effects of childbirth on maternal labor supply in Denmark, and Attanasio et al. (2025) compare subjective and experimental effects of maternal investments on child skill formation in Colombia.[8] We contribute by providing a design-based study of successive stages of college attendance, comparing levels and differences for two alternatives at the same admission margin. In

[7] Also called "*ex ante* returns" by Arcidiacono et al. (2020) and "subjective *ex ante* treatment effects" (S*ea*TE) by Giustinelli and Shapiro (2024). Giustinelli (2022) reviews analytic frameworks, measurement approaches, and empirical evidence in this literature, with a focus on education.

[8] McKenzie (2018) and Parker and Souleles (2019) present early attempts based on ex post beliefs.

particular, we introduce a potential outcomes framework that clarifies which subjective and objective objects are comparable for marginal applicants at a cutoff and develop formal decompositions that distinguish errors about admission from ones about take-up given admission and separate errors about unconditional enrollment from ones about completion conditional on enrollment. This enables us to move beyond documenting average forecast errors and identify which stage of the pipeline drives them.

Substantively, our findings speak to a growing literature on information frictions in centralized assignment (see reviews by Hakimov and Kübler, 2021; Rees-Jones and Shorrer, 2023; Che et al., 2025). Applicants misjudge their admission chances, which shapes which programs they list and how widely they search, and personalized information about admission chances can reduce application mistakes and improve placement (Kapor et al., 2020; Arteaga et al., 2022; Agte et al., 2024; Larroucau et al., 2025). Looking beyond admission, Larroucau and Rios (2024) show that initial assignments and learning after enrollment drive reapplication and switching, and that applicants anticipate lower first-year persistence in lower-ranked programs. We compare what applicants anticipate before admission decisions are announced, stage by stage, and under the preferred and alternative assignments, with outcomes identified at the admission margin, and find that the largest errors concern persistence after enrollment.

Experiments show that information about earnings, costs, or admission chances can change beliefs and educational choices (e.g., Jensen, 2010; Wiswall and Zafar, 2015a,b; Hastings et al., 2015; Baker et al., 2018; Conlon, 2021; Cattaneo and Wolter, 2022; Larroucau et al., 2025).[9] Some interventions provide information across fields of study (e.g., Wiswall and Zafar, 2015a,b), others focus on a subset (e.g., Conlon, 2021). We use the outcomes identified at the admission margin to correct applicants' beliefs, and a model of their rankings to predict how rankings respond when beliefs are corrected for one versus both programs. We show that correcting beliefs about one program can remove an error in comparisons that applicants make, as for enrollment errors in our data, or introduce one when errors across programs previously offset, as completion errors do in our data.

The remainder of the paper is organized as follows. Sections 2–5 describe the admissions system, framework, data, and identification. Section 6 compares subjective and objective counterfactuals and decomposes forecast errors, Section 7 examines the ranking implications of belief adjustments, and Section 8 concludes.

[9] Fuster and Zafar (2023) and Haaland et al. (2023) provide recent surveys extending beyond education.

2 Institutional Context

We study higher-education applications in Norway. Higher-education in Norway is an essentially public system where most degree programs (defined as a field-institution pair) follow a 3-year bachelor and 2-year master structure, while some integrated professional programs are longer. During our study period, higher education was largely tuition-free.[10]

The admission process operates through a centralized choice system, where qualified individuals can apply to nearly all universities and colleges through the centralized online portal of the Norwegian Universities and Colleges Admission Service (NUCAS, Samordna Opptak in Norwegian). Here they can list and rank up to 10 programs on the basis of their preferences. Applications open in early February and close around mid-April, although applicants can adjust their preference rankings until the first of July.[11] Applicants can find detailed information about all programs covered by the centralized system in a booklet that is distributed to all high schools every year.

Admissions are based on a serial dictatorship mechanism with a common priority ranking, which is theoretically strategy-proof and Pareto efficient (Svensson, 1999).[12] In practice, applicants are first ranked according to their application score, which equals high school GPA multiplied by 10 plus any supplementary points.[13] Applicants are then sequentially offered slots into programs, based on their application score, their previously submitted preferences for programs, and slot availability in those programs. That is, the applicant with the highest score is offered a slot in her first-choice program; the applicant with the second-highest score is offered a slot in her highest-ranked program for which there is a slot available; and so on. This process is repeated until slots, applicants, or both run out.

Based on this procedure, a first round of admission offers is issued to the applicants around the third week of July. They may accept an offer and, at the same time, accept a waiting-list position for a higher-priority program; applicants who later receive a higher-priority offer in the supplementary round may forfeit the earlier offer. In early August, the slots that are still vacant after the first round of admission offers are assigned to the waiting applicants through a second round of admission offers. By design, in the second round residual applicants are offered a higher-ranked program than in the first round or, at worst, the same program. Around mid-August, students start higher education in their accepted

[10] Most students attend public institutions and are eligible for loans and grants from the Norwegian State Educational Loan Fund.

[11] Between April and July, applicants may no longer add programs to their initial ranking, but can drop programs from it.

[12] The ten-program limit can affect ranking incentives, but most applicants list fewer than ten programs.

[13] High school grades range from 1 to 6. Supplementary points depend on selected high school subjects, underrepresentation in the program, age, prior education, and military service.

program. Students who wish to change to another over-subscribed program need to apply again the following year. If so, they participate again in the application and admission process on equal terms with the other applicants.

For the majority of programs there are more applicants than slots available. For such programs the margin of admission is defined by the application score of the last admitted applicant. Applicants with a score above this threshold are substantially more likely to enroll in the program than applicants with a marginally lower application score. This creates a standard fuzzy regression-discontinuity design. Kirkebøen et al. (2016) provide a more detailed contemporary description of the system and the implicit design.

3 Analytic Framework

To forecast enrollment and completion at the programs they apply to, applicants must assess their chances of admission, enrollment if admitted, and completion if enrolled. We define the corresponding potential outcomes and subjective beliefs, separately for applicants' first-choice and second-choice programs ($k = 1, 2$). We construct forecast errors (FEs) and derive two decompositions that quantify how discrepancies at successive stages can reinforce or offset one another.

Enrollment

First let $o_{ik} \in \{0,1\}$ indicate whether applicant i has an admission offer to her kth priority program, with $o_{ik} = 1$ denoting an offer (receipt of an offer of a place) and $o_{ik} = 0$ no offer. Applicant i's subjective assessment of $\Pr(o_{ik} = 1)$ after submitting her application but before learning whether she is admitted is denoted by $\omega_{ik} = \mathscr{E}_i[o_{ik}] \in [0,1]$, where $\mathscr{E}_i[\cdot]$ stands for i's subjective expectation given her information at elicitation.

After observing o_{ik} (and any other relevant state variables), the applicant decides whether or not to enroll in that program. Let $e_{ik}(\tilde{o}) \in \{0,1\}$ denote i's potential enrollment in her kth priority program given admission status $\tilde{o} \in \{0,1\}$. Let $e_{ik} \equiv e_{ik}(o_{ik}) \in \{0,1\}$ denote realized enrollment. Since it is not possible to enroll without admission, $e_{ik}(0) = 0$ for all i, k. The potential outcome $e_{ik}(1)$ is observed for applicants who are admitted, since then $e_{ik} = e_{ik}(1)$; for applicants without admission, it is counterfactual. The applicant's subjective assessment of $\Pr[e_{ik}(\tilde{o}) = 1]$ for $\tilde{o} \in \{0,1\}$ is denoted by $\varepsilon_{ik}(\tilde{o}) = \mathscr{E}_i[e_{ik}(\tilde{o})] \in [0,1]$. We assume $\varepsilon_{ik}(0) = 0$, reflecting that applicants understand that enrollment is impossible without an admission offer.

At elicitation, applicants may still be uncertain whether they would enroll if admitted.[14] We elicit applicants' subjective expectations $\mathscr{E}_i[\cdot]$ on a probabilistic scale from 0 to

[14] This is the "resolvable" uncertainty discussed by Blass et al. (2010).

100 percent. We do this for $k = 1, 2$ for all respondents before admission decisions are announced. Beliefs are therefore observed for everyone, including applicants who are not admitted.

The admission forecast error is realized admission minus its stated probability:

$$FE^{o}_{ik} = o_{ik} - \omega_{ik}. \tag{1}$$

This FE is observed for all applicants because both o_{ik} and ω_{ik} are observed for all applicants.

The forecast error for enrollment if admitted is potential enrollment under admission minus the stated probability of enrolling:

$$FE^{e|o}_{ik} = e_{ik}(1) - \varepsilon_{ik}(1). \tag{2}$$

The unconditional enrollment forecast error compares realized enrollment with its unconditional forecast:

$$FE^{e}_{ik} = e_{ik} - \omega_{ik}\varepsilon_{ik}(1), \tag{3}$$

where the forecast $\omega_{ik}\varepsilon_{ik}(1)$ is the stated probability of admission multiplied by the stated probability of enrolling if admitted.

A positive mean forecast error indicates that the outcome occurs more frequently than applicants predict on average; a negative mean indicates the reverse.

Since enrollment requires admission, realized enrollment is $e_{ik} = o_{ik}e_{ik}(1)$. We can express the unconditional enrollment FE in (3) as a function of the admission FE in (1) and the enrollment-if-admitted FE in (2). Simple algebra yields,

$$\begin{aligned} FE^{e}_{ik} &= [o_{ik} - \omega_{ik}]\varepsilon_{ik}(1) + o_{ik}[e_{ik}(1) - \varepsilon_{ik}(1)] \\ &\equiv \underbrace{FE^{o}_{ik}\varepsilon_{ik}(1)}_{\text{admission realization}} + \underbrace{o_{ik}FE^{e|o}_{ik}}_{\text{personal}}. \end{aligned} \tag{4}$$

This identity decomposes the forecast error in unconditional enrollment into two components. The first term (the admission realization component) tells us how much of the enrollment forecast error comes from the difference between anticipated and realized admission, rather than take-up after admission. It contains both ex ante admission-belief error and ex post admission surprise (Mueller and Spinnewijn, 2023). The second term (the "personal" component) isolates errors in predicting own take-up conditional on admission, holding admission status fixed. The personal component is zero for applicants who are not admitted.

Note that correct admission beliefs do not guarantee a zero admission realization

component among admitted applicants. An applicant who correctly reports a 50 percent chance of admission has an admission forecast error of $+0.50$ if admitted and -0.50 otherwise. Unconditionally, the expected error is zero. Conditioning on admission retains only the positive realization. The admission realization component weights this admission forecast error by the stated probability of enrolling if admitted. A positive mean among admitted applicants can therefore arise even when average admission beliefs are correct.

Completion

Let $c_{ik}(\tilde{e}) \in \{0,1\}$ indicate whether applicant i completes her kth priority program conditional on enrollment status $\tilde{e} \in \{0,1\}$. By construction, $c_{ik}(0) = 0$ for all i,k, since completion is impossible without enrollment. Let $c_{ik} \equiv c_{ik}(e_{ik}) \in \{0,1\}$ denote realized completion. Applicant i's subjective evaluation of $\Pr[c_{ik}(\tilde{e}) = 1]$ for $\tilde{e} \in \{0,1\}$ given her information set at the time of assessment is denoted by $\chi_{ik}(\tilde{e}) = \mathscr{E}_i\big[c_{ik}(\tilde{e})\big] \in [0,1]$. We assume that $\chi_{ik}(0) = 0$ and elicit $\chi_{ik}(1)$ probabilistically on a 0–100 scale. For forecast construction, we interpret $\varepsilon_{ik}(1)$ and $\chi_{ik}(1)$ as the subjective probabilities of enrolling conditional on admission and completing conditional on enrollment, respectively; the product forecasts then follow from the probability chain rule.

The forecast error for completion if enrolled is potential completion under enrollment minus the stated completion probability:

$$FE_{ik}^{c|e} = c_{ik}(1) - \chi_{ik}(1).$$

The unconditional completion forecast error compares realized completion with its unconditional forecast:

$$FE_{ik}^{c} = c_{ik} - \omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1), \tag{5}$$

where $\omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1)$ is the applicant's unconditional completion forecast, which is the stated probability of admission times the probability of enrolling if admitted times the probability of completing if enrolled.

We can decompose FE_{ik}^{c} into the component arising from errors in predicting completion conditional on enrollment and the remaining error in enrollment prediction. Noting $c_{ik} = e_{ik}c_{ik}(1)$ and using simple algebra, we obtain the following:

$$\begin{aligned} FE_{ik}^{c} &= e_{ik}c_{ik}(1) - \omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1) \\ &= [c_{ik}(1) - \chi_{ik}(1)]e_{ik} + \chi_{ik}(1)[e_{ik} - \omega_{ik}\varepsilon_{ik}(1)] \\ &\equiv \underbrace{FE_{ik}^{c|e}e_{ik}}_{\text{persistence}} + \underbrace{\chi_{ik}(1)FE_{ik}^{e}}_{\text{intention}}. \end{aligned} \tag{6}$$

In this decomposition, the first term (the "persistence" component) quantifies how much of the completion forecast error comes from differences between anticipated and realized completion after enrollment, holding realized enrollment fixed. The persistence component is zero for applicants who do not enroll. The second term (the "intention" component) tells us how much comes from enrollment turning out differently from anticipated, holding the stated complete-if-enrolled probability fixed. Since the enrollment forecast error FE^e_{ik} includes the admission realization component in (4), the intention component also contains admission surprise.

4 Data Sources and Description

Our empirical analysis relies on linking individual-level survey responses to administrative records.

Survey

The survey we fielded targeted 20,240 individuals born between 1997 and 1999, who applied to higher education in Norway in the spring of 2018 through NUCAS. We oversampled applicants whose 1st-choice program was predicted to be oversubscribed; 44% completed the survey.[15] Individuals were contacted by SMS with the link to the online survey. The survey was fielded in early July 2018, shortly after the final deadline for the 2018 application cycle, but before first-round admission offers were released. This yielded about 9,000 completed surveys from applicants to over 800 different study programs.

The main purpose of the survey was to elicit applicants' subjective expectations over outcomes associated with their 1st and 2nd priority in their college application.

Beliefs for binary outcomes were elicited using a numerical scale of percent chance ranging from 0 percent to 100 percent. In the analysis below, we focus on the following objects, with $k \in \{1,2\}$:

$$\Pr(i \text{ is admitted to } k\text{th priority} = 1);$$
$$\Pr(i \text{ enrolls in } k\text{th priority} = 1 \mid i \text{ is admitted to } k\text{th priority} = 1);$$
$$\Pr(i \text{ enrolls in } k\text{th priority} = 1);$$
$$\Pr(i \text{ graduates from } k\text{th priority} = 1 \mid i \text{ enrolls in } k\text{th priority} = 1);$$
$$\Pr(i \text{ graduates from } k\text{th priority} = 1),$$

[15] Sampling probabilities were 50%, 30%, and 10%. The analysis excludes the 10% stratum of applicants whose 1st-choice program was predicted not to be constrained and uses inverse-probability weights for the remaining strata.

where we directly elicit the 1st-choice admission probability, the 2nd-choice admission probability conditional on no 1st-choice admission, and the enrollment-if-admitted and completion-if-enrolled probabilities. We combine the two admission beliefs to construct the unconditional 2nd-choice admission probability. The unconditional enrollment and completion probabilities are constructed from the corresponding conditional probabilities.

Finally, the survey elicited expected annual earnings before taxes, in 2018 NOK, in the applicant's first job and at age 45 conditional on program completion, and the respondent's attitudes toward time, risk, and competition. See Appendix C for the questions.

Administrative Registers

Our analysis makes use of multiple registers of Norwegian administrative records. The first register is the universe of applications to higher education in Norway in 2018 which also contains formal enrollment in August. For the admission rates in Table 2, we record admission to the highest-ranked program for which the applicant received an offer during the admission cycle. An applicant who receives a second-choice offer and subsequently a first-choice offer is therefore recorded as admitted to her first choice. The second register is the Norwegian population registry, containing individuals' demographic and socioeconomic characteristics at age 16, including the person's gender and their mother's and father's education. We link the application and background information for the relevant set of applicants at the individual level.

We use the national education register from 2018 to 2024 to measure program completion. Completion requires a registered completion at the same institution and with the same NUS2000 program code as the application alternative. The outcome therefore measures completion of the program evaluated by the applicant, matching the elicited probability of completing that program conditional on enrollment.[16]

The elicited completion probabilities refer to eventual completion, and we observe education outcomes through 2024 (i.e., 6 years after enrollment). Appendix Figure A1 compares on-time completion across cohorts and first college completion by time since first enrollment. The 2018 completion trajectory is similar to those of surrounding cohorts, and most first college completions occur within six years.

Sample

Since the survey used a stratified sampling design with different selection probabilities across groups, the analysis uses inverse-probability weights, with each observation weighted by the reciprocal of its group-specific sampling probability. The analytic sam-

[16] We matched the education register's field classification to that of NUCAS.

ple retains applicants with observed 1st- and 2nd-choice programs, GPA-based 1st-choice admission, 1st-choice scores within 25 points of the cutoff, 1st-choice programs represented on both sides of the cutoff, and complete 1st-choice staged beliefs. Table 1 compares our sampling-weighted analytic survey sample of 7,469 applicants with comparable applicants in the population. It reports means and, for non-binary variables, standard deviations. Appendix Table A1 reports sample construction for each analysis; Appendix Table A3 summarizes admission outcomes.

The weighted survey sample closely resembles the population, with somewhat more women and higher application scores. 67% of sample applicants are female. 43% are 19 years old, 33% are 20 years old, and 24% are 21 years old. 61% are first-time applicants. 66% have at least one college-educated parent. The average application score is 46.5 and the standard deviation is 7.4. The risk-aversion/low-competitiveness and impatience scores are normalized to be mean zero and have standard deviations of 0.61 and 0.42, respectively.[17] People apply to a wide range of programs, which we group into five broad field-of-study categories, whose prevalence varies from 9 percent in Teaching to 36 percent in Health.

Table 2 compares subjective probabilities with realized admission, enrollment, and completion for applicants' 1st- and 2nd-choice programs. Beliefs and realizations are compared within the same groups: all applicants for admission, admitted applicants for enrollment, and enrolled applicants for completion. The table also reports enrollment-if-admitted and completion-if-enrolled beliefs for all applicants.

For the 1st-choice program the mean stated admission probability exceeds the admission rate by 12 percentage points (57 versus 45 percent). Among admitted applicants, the mean stated enrollment probability exceeds the enrollment rate by 8 percentage points (86 versus 78 percent). For applicants who enrolled the mean stated completion probability exceeds the completion rate by 25 percentage points (89 versus 64 percent).

For the 2nd-choice program, the enrollment gap among admitted applicants is 3 percentage points, and both the mean stated probability and the enrollment rate are lower (66 versus 63 percent). The completion gap for enrolled applicants is 40 percentage points (87 versus 47 percent), compared with 25 percentage points for the 1st choice.

For admission, we also distinguish between unconditional 2nd-choice beliefs and fallback beliefs, which condition on no admission to the 1st choice. On common outcome-and-forecast samples, applicants overpredict fallback admission by 16.3 percentage points and unconditional 2nd-choice admission by 1.7 percentage points. Beyond comparing means, we assess calibration: whether realized admission rates correspond to stated prob-

[17] These two scores are derived from a factor analysis applied to two measures of risk attitude (one self-reported and one task-based), two measures of time patience (one self-reported and one task-based), and a measure of attitude toward competition.

Table 1. Applicants' Characteristics

	Population (1)	Survey (2)
Female	0.62	0.67
Age 19	0.41	0.43
Age 20	0.34	0.33
Age 21	0.25	0.24
First-time applicant	0.60	0.61
At least one college-educated parent	0.65	0.66
Application score	44.7 (7.4)	46.5 (7.4)
Risk-aversion/low-competitiveness score (mean zero)	n.a.	0 (0.61)
Impatience score (mean zero)	n.a.	0 (0.42)
Field of study		
Social sciences and humanities	0.22	0.18
Science and engineering	0.16	0.20
Law and business	0.18	0.16
Teaching	0.12	0.09
Health	0.32	0.36
N	49,172	7,469

Note: The population comprises 2018 first-choice applicants aged 19-21 with a valid application score and a matched admission cutoff. Survey statistics use inverse sampling-probability weights. Standard deviations are in parentheses. The factor scores are observed only in the survey; N is 6,378 for these measures.

abilities. We regress admission indicators on stated probabilities and jointly test an intercept of zero and a slope of one. We reject this hypothesis for 1st-choice admission, fallback admission, and unconditional 2nd-choice admission.[18] Appendix Table A2 reports the accuracy, calibration, and predictability tests. Appendix Figure A11 plots realized admission rates against stated probabilities.

Reported probabilities vary substantially across applicants, and many applicants report certainty about their admission, enrollment, and completion prospects. In particular, 30% of sample applicants expect to be admitted to their 1st-choice program with certainty, 13% expect not to be admitted with certainty, whereas the remaining 57% of applicants express uncertainty about their admission prospects by reporting a subjective probability strictly interior to the 0-100 percent-chance range. For the constructed unconditional 2nd-choice admission probability, the corresponding figures are 3%, 36%, and 61%. The share with an uncertain admission forecast is therefore similar across choices, but for the 2nd choice certainty of admission is less common and certainty of rejection more common.

Among applicants admitted to their 1st-choice program, 70% had reported a 100 percent chance of enrolling if admitted, 24% an interior probability, and 6% a zero percent

[18]For rational-expectations tests, see Muth (1961); Lovell (1986); Pesaran and Weale (2006); D'Haultfoeuille et al. (2021); Crossley et al. (2024).

Table 2. Applicants' Outcomes: Subjective Probabilities and Realizations

	1st-choice program				2nd-choice program			
	Mean (1)	SD (2)	% at 0 (3)	% at 100 (4)	Mean (5)	SD (6)	% at 0 (7)	% at 100 (8)
A. Admission								
Subjective (all)	0.57	0.40	13	30	0.23	0.30	36	3
Actual (all)	0.45	-	-	-	0.21	-	-	-
B. Enrollment if admitted								
Subjective (admitted)	0.86	0.30	6	70	0.66	0.38	13	42
Subjective (all)	0.79	0.35	8	63	0.61	0.40	19	38
Actual (admitted)	0.78	-	-	-	0.63	-	-	-
C. Completion if enrolled								
Subjective (enrolled)	0.89	0.16	0	42	0.87	0.20	0	48
Subjective (all)	0.91	0.17	0	53	0.86	0.22	2	47
Actual (enrolled)	0.64	-	-	-	0.47	-	-	-
N	7,469				5,902			

Note: Statistics use survey sampling weights and a common complete-case sample within each choice. Rows marked "all" include all applicants, and rows marked "admitted" or "enrolled" restrict the sample to applicants who were admitted or enrolled in the indicated program.

chance. For applicants admitted to their 2nd-choice program, the corresponding shares are 42%, 45%, and 13%. Uncertainty about enrollment is therefore more common for the 2nd choice. The same pattern holds in the full sample where 29% report an interior probability for their 1st choice, compared with 43% for their 2nd choice.

Among applicants who enrolled in their 1st-choice program, fewer than 1% had reported a zero percent chance of completion, 42% a 100 percent chance, and the remaining 58% an interior probability. Among applicants who enrolled in their 2nd-choice program, 48% had reported a 100 percent chance of completion.

5 The Role of the Research Design

The Norwegian centralized application-and-admission system generates implicit admission cutoffs whose exact values are unknown to the applicants, effectively randomizing students with scores near the cutoff into different programs. We use this variation to compare applicants' subjective beliefs with estimates of enrollment and completion under 1st- and 2nd-choice admission.

We apply linear two-stage least squares (2SLS) throughout, using the indicator for being above the 1st-choice cutoff as an instrument for admission. Local-polynomial RD is used as a diagnostic. The design delivers: (i) local average treatment effects (LATEs)

of access on enrollment and completion; (ii) potential-outcome levels for compliers under access, which we report both for compliers and, where identified, for principal strata tied to the 2nd-choice counterfactual.

Identification

The survey elicits enrollment-if-admitted and completion-if-enrolled beliefs for applicants' 1st- and 2nd-choice programs. We use the admission cutoffs to obtain outcome benchmarks for these beliefs.

We use the single-admission feature of the mechanism to define principal strata at the 1st-choice cutoff. To simplify notation, in this subsection we omit the i subscript. Let $Z_1 \in \{0,1\}$ indicate whether the applicant is (locally) above her 1st-choice cutoff, with $Z_1 = 1$ denoting above cutoff and $Z_1 = 0$ below cutoff. Further, let

$$D(z_1) \in \{0,1,2\}$$

denote the admission state the applicant would obtain under $Z_1 = z_1$, where $D = 1$ corresponds to admission to the 1st-ranked program, $D = 2$ to admission to the 2nd-ranked program, and $D = 0$ to no admission to either the 1st- or 2nd-ranked program. For an outcome Y (enrollment or completion), let Y^d denote the potential outcome under admission state $D = d$, which is the object directly matched to the elicited beliefs "if admitted to the 1st/2nd choice." For enrollment, Y^k corresponds to $e_{ik}(1)$ in Section 3, for $k = 1,2$.

Principal strata are defined by the pair $\{D(0), D(1)\}$ (Frangakis and Rubin, 2002; Imbens and Rubin, 1997, 2015). Table 3 lists all logical types; entries "struck through" are ruled out by the single-admission constraint and monotonicity at the first-choice cutoff. Locally, we assume $D(1) \in \{1, D(0)\}$: crossing the 1st-choice cutoff either results in 1st-choice admission or leaves the fallback state unchanged. This excludes switches between no top-two admission and 2nd-choice admission at that cutoff. Relative to the textbook case with binary assignment and binary treatment, we have two kinds of compliers ($C2$ and $C0$), three kinds of always-takers ($A1$, $A2$, and $A0$), two kinds of never-takers ($X2$ and $X0$), and two kinds of defiers ($DF2$ and $DF0$). Focusing on compliers, our main types of interest, both $C2$ and $C0$ applicants would be admitted to their 1st-choice program if $Z_1 = 1$, but would end up in different admission states otherwise: $C2$ types would be admitted to their 2nd-ranked program, whereas $C0$ types would either be admitted to a lower ranked program or not admitted at all. Our 1st-versus-2nd-choice comparison requires both potential outcomes for the same $C2$ applicants.

Let $p^{C2} = \Pr(C2)$ and $p^{C0} = \Pr(C0)$ denote the local shares (near the 1st-choice cutoff) of strata $C2$ and $C0$. Define $D_j \equiv \mathbf{1}\{D = j\}$ for $j \in \{0,1,2\}$, so that $D_k = o_{ik}$ for $k = 1,2$.

Table 3. Principal Strata Defined by $D(0)$ and $D(1)$

A. Principal strata		
	Below cutoff $D(0)$	Above cutoff $D(1)$
C2	2	1
C0	0	1
A1	1	1
A2	2	2
A0	0	0
X2	0	2
X0	2	0
DF2	1	2
DF0	1	0

B. Observed groups		
	Below cutoff $Z_1 = 0$	Above cutoff $Z_1 = 1$
$D = 1$	A1, ~~DF2, DF0~~	A1, C2, C0
$D = 2$	A2, C2, ~~X0~~	A2, ~~DF2, X2~~
$D = 0$	A0, C0, ~~X2~~	A0, ~~DF0, X0~~

Note: DF2, DF0, X2, and X0 are ruled out by the single-admission restriction and monotonicity.

The stratum shares are identified directly from first stages, as follows:

$$\begin{aligned} E[D_1 \mid Z_1 = 1] - E[D_1 \mid Z_1 = 0] &= p^{C0} + p^{C2}, \\ E[D_2 \mid Z_1 = 0] - E[D_2 \mid Z_1 = 1] &= p^{C2}, \\ E[D_0 \mid Z_1 = 0] - E[D_0 \mid Z_1 = 1] &= p^{C0}, \end{aligned}$$

where $D_0 \equiv \mathbf{1}\{D = 0\}$.

Write

$$p \equiv \frac{p^{C0}}{p^{C0} + p^{C2}} = \frac{E[D_0 \mid Z_1 = 0] - E[D_0 \mid Z_1 = 1]}{E[D_1 \mid Z_1 = 1] - E[D_1 \mid Z_1 = 0]},$$

for the $C0$ weight among 1st-choice compliers.

Because D_2 falls at the 1st-choice cutoff for $C2$, we use the sign-flipped pair $\{-Y \cdot D_2, -D_2\}$, so the first stage is positive, and obtain,

$$\begin{aligned} E[-Y \cdot D_2 \mid Z_1 = 1] &= -E[Y^2 \mid A2] \Pr(A2), \\ E[-Y \cdot D_2 \mid Z_1 = 0] &= -E[Y^2 \mid A2] \Pr(A2) - E[Y^2 \mid C2] \Pr(C2), \\ E[-D_2 \mid Z_1 = 1] &= -\Pr(A2), \qquad E[-D_2 \mid Z_1 = 0] = -\Pr(A2) - \Pr(C2). \end{aligned}$$

The above equations yield,

$$\frac{E[-Y \cdot D_2 \mid Z_1 = 1] - E[-Y \cdot D_2 \mid Z_1 = 0]}{E[-D_2 \mid Z_1 = 1] - E[-D_2 \mid Z_1 = 0]} = E[Y^2 \mid C2].$$

An entirely analogous argument with $\{-Y \cdot D_0, -D_0\}$ identifies $E[Y^0 \mid C0]$.[19]

[19] The conventional Wald ratio of the cutoff differences in Y and D_1 averages $E[Y^1 - Y^0 \mid C0]$ and $E[Y^1 - Y^2 \mid C2]$ with weights p and $1 - p$.

Using the fact that $A1$ types contribute $D_1 = 1$ on both sides (and thus cancel in a difference), the Wald ratio from 2SLS with $Y \cdot D_1$ as the dependent variable,

$$\begin{aligned} E[Y \cdot D_1 \mid Z_1 = 1] &= E[Y^1 \mid C0]\, p^{C0} + E[Y^1 \mid C2]\, p^{C2} \\ &\quad + E[Y^1 \mid A1] \Pr(A1), \\ E[Y \cdot D_1 \mid Z_1 = 0] &= E[Y^1 \mid A1] \Pr(A1), \\ \frac{E[Y \cdot D_1 \mid Z_1 = 1] - E[Y \cdot D_1 \mid Z_1 = 0]}{E[D_1 \mid Z_1 = 1] - E[D_1 \mid Z_1 = 0]} &= E[Y^1 \mid C0]\; p + E[Y^1 \mid C2]\; (1-p), \end{aligned} \tag{7}$$

identifies the complier-share weighted 1st-choice mean for the pooled $C2, C0$ complier group.

$E[Y^1 \mid C2]$ is not separately identified because this pooled mean also includes $C0$ applicants. We therefore restrict the sample to applicants who are above the 2nd-choice cutoff and within five score points of the 1st-choice cutoff; observations exactly at the 1st-choice cutoff are excluded. The first-stage estimates imply that p^{C0} is approximately 0.02, which means that the mixture weight $p = p^{C0}/(p^{C0} + p^{C2})$ is very small and therefore that the identified complier mean under $D = 1$ is numerically close to $E[Y^1 \mid C2]$.

We also report no-assumption bounds for the $C2$-specific 1st-choice level and first-minus-second contrast. These are obtained by combining the identified mixture with the bounds on $Y^1 \in [0,1]$. Specifically, if $m \equiv p\,E[Y^1 \mid C0] + (1-p)\,E[Y^1 \mid C2]$ denotes the identified mixture in (7), then

$$E[Y^1 \mid C2] \in \left[\max\left\{0, \frac{m-p}{1-p}\right\},\; \min\left\{1, \frac{m}{1-p}\right\} \right]. \tag{8}$$

These bounds are reported in square brackets in the principal-strata tables above.

Estimation

We estimate the objects of interest using linear 2SLS regressions, with local controls $g(h)$ defined below. Depending on the estimand, the endogenous regressor is either the 1st-choice admission indicator D_{1i} (admission-based estimands) or enrollment (enrollment-based estimands). The dependent variable is enrollment, completion, or the corresponding belief measure. The belief measures are $\varepsilon_{ik}(1)$ for enrollment if admitted, $\varepsilon_{ik}(1)\chi_{ik}(1)$ for completion if admitted, and $\chi_{ik}(1)$ for completion if enrolled. Using the same window and controls puts each objective outcome and its belief counterpart at the same local margin.

Applicants i submit a ranked list of programs. Let h_i denote applicant i's application score minus the cutoff for her 1st-choice program and $Z_{1i} = \mathbf{1}\{h_i \geq 0\}$ the threshold indicator (Z_1 in the identification discussion above, with indexing restored). Let $D_{1i} \in$

$\{0,1\}$ indicate admission to the 1st-ranked program and $D_{2i} \in \{0,1\}$ admission to the 2nd-ranked program. The centralized mechanism yields admission to at most one program locally, so $D_{1i}D_{2i} = 0$. Outcomes $Y_i \in \{0,1\}$ include enrollment and completion.

For a given outcome Y, within a symmetric window around $h_i = 0$, we estimate,

$$Y_i = \alpha + \tau D_{1i} + g(h_i) + u_i, \tag{9}$$

$$D_{1i} = \gamma + \pi Z_{1i} + g(h_i) + v_i, \tag{10}$$

by 2SLS, where $g(h)$ is a low-order polynomial in h interacted with $\mathbf{1}\{h \geq 0\}$ (quadratic in the baseline). The coefficient τ is a pooled FRDD estimand that can be interpreted as a weighted average of program-specific LATEs of 1st-choice admission on Y at the cutoff under standard assumptions (continuity, monotonicity, exclusion).

In addition to potential-outcome contrasts, our comparisons of interest require potential-outcome levels. These are functions of the same local reduced-form moments and are computed using the same window and controls. In particular, we estimate the moments entering the Wald ratios above by running the same local specifications with dependent variables $Y_i D_{ji}$ and D_{ji} for $j \in \{0,1,2\}$, where $D_{0i} \equiv \mathbf{1}\{D_{1i} = 0,\ D_{2i} = 0\}$.

For Complete if enrolled, the complier groups are defined by enrollment responses to the cutoff rather than admission responses. We divide the cutoff-induced change in the product of completion and enrollment by the corresponding change in enrollment. Under local continuity, monotonicity of enrollment in the relevant direction, and exclusion of a direct effect of the instrument on completion holding enrollment fixed, this identifies completion among admission-induced enrollees.[20]

For descriptive comparisons for the admitted ("all treated") group, we report conditional means $E[Y_i \mid D_{ji} = 1]$ and the corresponding beliefs in the full analysis sample (for $j = 1$ or $j = 2$), without a causal interpretation. Appendix Table A5 compares observed characteristics across the marginal, all treated, and full applicant groups.

We conduct standard RD diagnostics. These include a density test for manipulation around the admission cutoff in Appendix Figure A3; balance tests for predetermined characteristics and discontinuity tests for subjective expectations at the cutoff in Appendix Table A4 and Appendix Figures A4 and A5; and discontinuity tests for actual admission, enrollment, and completion in Appendix Figure A6. As a robustness exercise, in Appendix Table A7 we re-estimate enrollment if admitted and its forecast error using bias-aware local-linear regression with MSE-optimal bandwidths, based on Kolesár and Rothe (2018)'s `rdhonest`. These estimates are close to the baseline 2SLS results. First-choice

[20] The formal-enrollment first stages are 0.619 (SE 0.044) and 0.515 (SE 0.044) for the 1st and 2nd choices; the corresponding completion-times-enrollment reduced forms are 0.346 (SE 0.047) and 0.231 (SE 0.040).

admission beliefs rise sharply near the cutoff, although the discrete running variable does not allow us to distinguish a discontinuity from steep local curvature. Enroll-if-admitted and complete-if-enrolled beliefs are smooth at the cutoff.

6 Forecasting Getting In and Getting Through

Beliefs and Counterfactual Outcomes

Applicants forecast enrollment reasonably well but completion poorly, and their errors affect the comparison between programs in opposite ways. Table 4 compares subjective beliefs with the corresponding objective outcomes for Enroll if admitted, Complete if admitted, and Complete if enrolled. For the first two measures, the 1st-choice point estimates refer to pooled $C2C0$ applicants and the 2nd-choice estimates to $C2$; for Complete if enrolled, the analogous strata are defined by enrollment responses to the cutoff. The $C0$ share is small, and the $C2$ bounds leave the substantive comparisons unchanged.

Enrollment errors are small at each program but have opposite signs, so they increase the error in the difference between programs. For formal enrollment in August, applicants overpredict enrollment if admitted to their 1st-choice program by 7 percentage points (0.85 versus 0.78) and underpredict it at their 2nd choice by 7 points (0.60 versus 0.67). The subjective first-minus-second difference is therefore 0.25, compared with an objective difference of 0.11, a gap of 0.14 (SE 0.06, p = 0.02). The $C2$ bounds for enrollment if admitted are narrow.

Completion errors are large at each program but have the same sign, so they partly offset in the difference between programs. This holds whether completion is measured after admission or after enrollment, and is consistent with earlier evidence that students overpredict college completion (Fischhoff et al., 2000; Cowan, 2018). Complete if admitted depends on enrollment behavior. Conditional on admission, applicants expect to complete with probability 0.77 if admitted to their 1st choice and 0.53 if admitted to their 2nd, compared with objective rates of 0.44 and 0.30. These objective-minus-subjective differences by program (0.33 and 0.23, in absolute value) result in an error of 0.10 in the contrast between the two programs (SE 0.08, p = 0.20). Complete if enrolled isolates persistence after enrollment. Keeping enrollment fixed, applicants expect to complete with probability 0.91 at their 1st choice and 0.85 at their 2nd, compared with objective rates of 0.56 and 0.45. These objective-minus-subjective differences by program (0.35 and 0.40) nearly cancel across the two programs, leaving an error of -0.05 in the difference (SE 0.09, p = 0.55). All four program-specific gaps are statistically significant ($p < 0.001$). The $C2$ bounds are consistent with this pattern; they are narrow for Complete if admitted and wider for Complete if enrolled.

Table 4. Subjective and Objective Potential Outcomes and 1st vs 2nd Choice Differences among Marginal Applicants

	Enroll if admitted			Complete if admitted			Complete if enrolled		
	Subj. (1)	Obj. (2)	Diff. (3)	Subj. (4)	Obj. (5)	Diff. (6)	Subj. (7)	Obj. (8)	Diff. (9)
1st choice	0.85	0.78	0.07	0.77	0.44	0.33	0.91	0.56	0.35
	(0.03)	(0.05)	(0.04)	(0.03)	(0.06)	(0.06)	(0.02)	(0.06)	(0.06)
		[.78, .81]			[.42, .45]			[.47, .67]	
2nd choice	0.60	0.67	-0.07	0.53	0.30	0.23	0.85	0.45	0.40
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	(0.06)	(0.06)
1st − 2nd	0.25	0.11	0.14	0.24	0.14	0.10	0.06	0.11	-0.05
	(0.05)	(0.07)	(0.06)	(0.05)	(0.08)	(0.08)	(0.03)	(0.09)	(0.09)
		[.11, .14]			[.13, .16]			[.02, .22]	

Note: Enroll if admitted, Complete if admitted, and Complete if enrolled denote $e_{ik}(1)$, $c_{ik}(e_{ik}(1))$, and $c_{ik}(1)$; their subjective counterparts are $\varepsilon_{ik}(1)$, $\varepsilon_{ik}(1)\chi_{ik}(1)$, and $\chi_{ik}(1)$. Enrollment is formal registration in August. Point-identified 1st-choice levels refer to C2C0 and 2nd-choice levels to C2; subjective and objective levels are matched within each stratum and use the common complete-case sample for each comparison. For Complete if enrolled, strata are defined by enrollment responses to the cutoff. Standard errors from the joint bootstrap are in parentheses below estimates. Square brackets report C2-specific bounds for the objective 1st-choice level and the objective 1st-minus-2nd difference from Eq. (8). Appendix Table A6 and Figure A7 report completion-if-admitted estimates for other samples and principal strata.

The point estimates suggest that first-choice admission raises enrollment and completion at the margin (0.11 and 0.14). The cross-program contrast in completion if enrolled is 0.11. Applicants expect larger differences in enrollment and completion if admitted (0.25 and 0.24), but a smaller difference in completion if enrolled (0.06). The point-estimate pattern is consistent with an exaggerated perceived enrollment difference contributing to the overstatement of the completion-if-admitted difference.

We reject mean accuracy for completion levels at both programs and for the first-minus-second enrollment difference, but not for the first-minus-second completion differences.

Applicants' own take-up errors are modest, while their persistence errors are large for both programs. Comparisons conditional on admission or enrollment do not show whether errors at successive stages reinforce or offset one another in applicants' unconditional forecasts. We therefore decompose unconditional enrollment and completion forecast errors by stage. Throughout, forecast errors (FE) are defined as actual minus expected. Comparisons that condition on the realized admission outcome mix ex ante bias with how admissions turned out, and the cutoff design does not separate the two.

Enrollment Forecast Errors

Most of the unconditional enrollment forecast error comes from admission; take-up errors are modest. Equation (4) decomposes the unconditional enrollment forecast error into two weighted stage contributions. The admission realization component, $\varepsilon_{ik}(1)FE^{o}_{ik}$, weights the admission forecast error by the stated enrollment-if-admitted probability. The personal component, $o_{ik}FE^{e|o}_{ik}$, contributes take-up forecast errors only for admitted applicants.[21] Table 5 reports the mean contributions and their sum for both programs, separately for marginal applicants and all admitted applicants.

For the 1st-choice program, small errors at the two stages offset, leaving a small total. For marginal applicants, the admission realization component is $+0.09$ and statistically different from zero. The personal component is -0.07, implying modest overprediction of take-up conditional on admission (consistent with the negative enrollment-if-admitted forecast errors in Appendix Table A7). The total unconditional enrollment FE is about $+0.02$.[22] Among all admitted applicants, the admission realization component remains positive ($+0.07$), while the personal component is more negative (-0.08), yielding a total FE close to zero.

For the 2nd-choice program, the total unconditional enrollment FE is large, mainly because enrollment under 2nd-choice admission is compared with a forecast that also allows for not receiving that offer. Among marginal applicants, the admission realization component is $+0.34$ and the personal component is $+0.07$, implying a total of about $+0.41$. The positive personal component indicates underprediction of take-up conditional on being admitted to the 2nd-choice program (consistent with the positive enrollment-if-admitted forecast errors in Appendix Table A7). Among all admitted applicants, the admission realization component remains sizeable ($+0.26$), but the personal component is negative (-0.03). Overprediction of take-up conditional on a second-choice admission therefore partially offsets the admission realization component, and the total FE remains positive at $+0.23$.

Most of the admission realization contribution disappears when the forecast conditions on not being admitted to the 1st choice. When we replace the unconditional 2nd-choice admission belief with the elicited fallback belief, the admission realization component falls from 0.34 to 0.02 for marginal applicants and from 0.26 to 0.06 for all admitted applicants, while the personal components are unchanged. Appendix Figure A9 shows the unconditional-forecast decomposition, with the admission realization component varying more with distance to the cutoff than the personal component. Appendix Table A8 reports

[21] Appendix Table A7 reports actual and expected enrollment if admitted and their difference; Appendix Figure A8 plots these quantities by distance from the cutoff.

[22] The decomposition is exact for the 2SLS estimates, but only approximate for the nonparametric estimates, as we do not constrain bandwidths to be equal across components.

Table 5. Decomposition of Unconditional Enrollment Forecast Error (FE): Admission Realization vs Personal (enrollment if admitted) Components

	Marginal applicants		All treated
	2SLS FE (1)	Local linear FE (2)	Mean FE (3)
A. 1st-choice program			
(a) Admission realization	0.09	0.08	0.07
	(0.02)	(0.03)	(0.00)
(b) Personal	-0.07	-0.06	-0.08
	(0.03)	(0.03)	(0.01)
(c) Total forecast error	0.02	0.03	-0.00
	(0.04)	(0.03)	(0.01)
N	2,746		3,365
B. 2nd-choice program			
(a) Admission realization	0.34	0.33	0.26
	(0.03)	(0.03)	(0.01)
(b) Personal	0.07	0.07	-0.03
	(0.05)	(0.05)	(0.01)
(c) Total forecast error	0.41	0.40	0.23
	(0.05)	(0.05)	(0.01)
N	2,144		1,245

Note: Components follow Eq. (4); negative forecast errors indicate overprediction. Column (1) uses local quadratic 2SLS; column (2) uses local-linear `rdhonest` estimates with MSE-optimal bandwidths (Kolesár and Rothe, 2018). Column (3) reports means among applicants admitted to the indicated program. Estimates use survey sampling weights; standard errors are in parentheses.

the corresponding MSE decomposition.

Completion Forecast Errors

Applicants substantially overpredict completion conditional on enrollment for both programs and in both applicant groups. Equation (6) decomposes the unconditional completion forecast error into two weighted stage contributions. The intention component, $\chi_{ik}(1)FE^{e}_{ik}$, weights the enrollment forecast error just analyzed by the stated completion-if-enrolled probability. The persistence component, $e_{ik}FE^{c|e}_{ik}$, contributes completion-if-enrolled forecast errors only for applicants who enroll. Table 6 reports the mean contributions and their sum for the same program and applicant groups.

For the 1st-choice program, completion FEs are driven overwhelmingly by persistence. The intention component is small: $+0.02$ for marginal applicants and close to zero for all admitted applicants, mirroring the sign differences in the unconditional enrollment FEs in Table 5. The persistence component is large and negative in both samples, -0.26 for marginal applicants and -0.19 for all admitted applicants. As a result, the total un-

conditional completion FE is large and negative, about -0.24 for marginal applicants and -0.20 for all admitted applicants.

For the 2nd-choice program, the intention component is large and positive, mainly because realized enrollment is compared with an unconditional forecast that allows for not being admitted to the 2nd choice. The component is $+0.34$ for marginal applicants and $+0.20$ for all admitted applicants, consistent with the sizeable positive unconditional enrollment FEs for 2nd-choice admissions in Table 5. The persistence component remains negative and sizeable, about -0.27 for marginal applicants and -0.25 for all admitted applicants. Among marginal applicants, the two components largely offset each other, leaving a small positive total unconditional completion FE of $+0.07$. Among all admitted applicants, persistence dominates the intention component, yielding a negative total FE of about -0.06.

Most of the positive intention contribution disappears when the forecast conditions on not being admitted to the 1st choice. With conditional fallback beliefs, the 2nd-choice intention component falls from 0.34 to 0.06 for marginal applicants and from 0.20 to 0.02 for all admitted applicants. The persistence components are unchanged, so persistence overprediction remains under the conditional forecast.

The decomposition shows how these stage-specific discrepancies combine in the unconditional completion forecast error but does not distinguish their underlying mechanisms.[23] Appendix Figure A10 reports the same decomposition by distance to the cutoff. Appendix Table A9 reports the corresponding MSE decomposition.

Heterogeneity in Forecast Errors

Persistence contributions are substantial and negative in every subgroup we examine, for both programs and among both marginal and all admitted applicants. We examine heterogeneity by gender, parental education (at least one college-educated parent), application experience (first-time versus repeat applicants), application score (above versus at or below the median of 46.4), patience, and risk tolerance. Appendix Tables A10–A21 report the full enrollment and completion decompositions.

7 Implications for Program Rankings

Do these forecast errors change which program applicants rank first? We use a fitted choice model to compare corrections to one program with corrections to both, holding program attributes and admission cutoffs fixed.

[23] Earlier work points to underappreciation of college demands (Reynolds and Pemberton, 2001), overly optimistic beliefs about academic ability (Stinebrickner and Stinebrickner, 2012), and learning about academic performance (Stinebrickner and Stinebrickner, 2014a,b).

Table 6. Decomposition of Unconditional Completion Forecast Error (FE): Intention (Enroll) vs Persistence (completion if enrolled) Components

	Marginal applicants		All treated
	2SLS FE (1)	Local linear FE (2)	Mean FE (3)
A. 1st-choice program			
(a) Intention	0.02	0.03	-0.00
	(0.03)	(0.03)	(0.01)
(b) Persistence	-0.26	-0.25	-0.19
	(0.05)	(0.04)	(0.01)
(c) Total forecast error	-0.24	-0.22	-0.20
	(0.05)	(0.04)	(0.01)
N	2,746		3,364
B. 2nd-choice program			
(a) Intention	0.34	0.33	0.20
	(0.04)	(0.05)	(0.01)
(b) Persistence	-0.27	-0.27	-0.25
	(0.05)	(0.03)	(0.01)
(c) Total forecast error	0.07	0.09	-0.06
	(0.05)	(0.05)	(0.01)
N	2,142		1,244

Note: Components follow Eq. (6); negative forecast errors indicate overprediction. Realized completion counts only applicants who formally enrolled in that program in August 2018. Column (1) uses local quadratic 2SLS; column (2) uses local-linear `rdhonest` estimates with MSE-optimal bandwidths (Kolesár and Rothe, 2018). Column (3) reports means among applicants admitted to the indicated program. Estimates use survey sampling weights; standard errors are in parentheses.

Approach

As before, $k = 1$ denotes the applicant's 1st-choice program and $k = 2$ the relevant 2nd-choice alternative. For each alternative $k \in \{1,2\}$, we observe the beliefs introduced in Section 3: the subjective probability of admission, ω_{ik}; the subjective probability of enrollment given admission, $\varepsilon_{ik}(1)$; and the subjective probability of completion given enrollment, $\chi_{ik}(1)$.

We estimate a pairwise choice model for the observed top-two ordering, using a conditional logit with applicant-specific choice sets of size two. Let V_{ik} denote the deterministic component of applicant i's utility over alternative $k \in \{1,2\}$. The model implies,

$$P_i \equiv \Pr(1_i \succ 2_i) = \frac{\exp(V_{i1})}{\exp(V_{i1}) + \exp(V_{i2})}. \tag{11}$$

Let $q_{ik} = \varepsilon_{ik}(1)\chi_{ik}(1)$ denote the subjective probability of completing program k conditional on admission, and let w_{ik} denote expected earnings at age 45 conditional on com-

pletion. Our main specification is

$$V_{ik} = \beta_q q_{ik} + \gamma_w \log(w_{ik}) + x'_{ik}\gamma. \tag{12}$$

The vector x_{ik} contains field indicators and distance controls. While this specification allows the probability of completing if admitted and expected earnings conditional on completion to impact rankings, it does not control for admission beliefs since these should not matter for rankings in a strategy-proof mechanism. We report results below relaxing this assumption.

We adjust beliefs about enrollment if admitted ($\varepsilon_{ik}(1)$) and completion if enrolled ($\chi_{ik}(1)$) by their rank-specific objective-minus-subjective mean gaps. Let $T(x) \equiv \min\{1, \max\{0, x\}\}$ denote truncation to $[0,1]$. For $k \in \{1,2\}$, define the adjusted beliefs, denoted by the superscript *corr*, as,

$$\varepsilon_{ik}^{corr}(1) = T\left(\varepsilon_{ik}(1) + \widehat{FE}_k^{e|o}\right), \tag{13}$$

$$\chi_{ik}^{corr}(1) = T\left(\chi_{ik}(1) + \widehat{FE}_k^{c|e}\right). \tag{14}$$

Here, $\widehat{FE}_k^{e|o}$ is the admission-margin gap in take-up conditional on admission, and $\widehat{FE}_k^{c|e}$ is the corresponding persistence gap among admission-induced enrollees. The ranking corrections use conditional mean forecast errors. Section 6 reports their weighted contributions to unconditional forecast errors.

We consider take-up and persistence adjustments separately and jointly. For each adjustment, we change beliefs for the 1st-choice program only, the 2nd-choice program only, or both programs. All other beliefs remain unchanged.

For each adjustment case s, we form adjusted deterministic utility indices by replacing the relevant belief components in (12) with their adjusted counterparts, holding the estimated coefficients fixed. Let

$$\widehat{P}_i^{base} = \Lambda\left(\widehat{V}_{i1}^{base} - \widehat{V}_{i2}^{base}\right), \qquad \widehat{P}_i^{s} = \Lambda\left(\widehat{V}_{i1}^{s} - \widehat{V}_{i2}^{s}\right), \tag{15}$$

where $\Lambda(v) = \exp(v)/(1+\exp(v))$. These are the baseline and adjusted fitted probabilities that applicant i ranks her 1st choice above her 2nd choice.

The take-up adjustment is estimated for admission compliers, and the persistence adjustment for admission-induced enrollees, at the 1st-choice admission cutoff. We evaluate ranking responses for admission compliers using Abadie (2003) kappa weights. Let $D_{1i} \in \{0,1\}$ indicate whether applicant i was admitted to her 1st-choice program. Let $\hat{p}$ denote the sampling-weighted share of applicants with $Z_{1i} = 1$ in the local estimation sample. Under a local-randomization interpretation, $\hat{p}$ estimates $\Pr(Z_{1i} = 1)$. The weight

is

$$\kappa_i = 1 - \frac{D_{1i}(1 - Z_{1i})}{1 - \hat{p}} - \frac{(1 - D_{1i})Z_{1i}}{\hat{p}}.$$

We use the κ_i weights and multiply them by the survey sampling weights. Under the local-randomization interpretation and the standard IV assumptions, $E[\kappa_i g_i]/E[\kappa_i]$ identifies the corresponding complier mean for any integrable g_i.

Let a_i denote the product of the Abadie and survey sampling weights. For each adjustment case s, the reported rank response is

$$\widehat{\Delta P}^s = \frac{\sum_i a_i \left(\widehat{P}_i^s - \widehat{P}_i^{base} \right)}{\sum_i a_i},$$

and negative values therefore indicate that the adjustment decreases the fitted probability of ranking the current 1st choice above the 2nd.

We also compute the change in log expected 1st-choice earnings that compensates for the enrollment and completion belief adjustments by restoring the baseline average fitted ranking. The compensating expected-earnings differential, δ^s, is measured in log units and solves

$$\frac{\sum_i a_i \Lambda\left(\widehat{V}_{i1}^s - \widehat{V}_{i2}^s + \widehat{\gamma}_w \delta^s \right)}{\sum_i a_i} = \frac{\sum_i a_i \Lambda\left(\widehat{V}_{i1}^{base} - \widehat{V}_{i2}^{base} \right)}{\sum_i a_i}.$$

A positive value of δ^s indicates that expected 1st-choice earnings must increase relative to the 2nd choice to offset the fitted-ranking effects of the belief adjustment.

We bootstrap standard errors where we keep the stage-specific mean adjustments fixed and re-estimate the ranking model, Abadie weights, rank response and earnings differential on each replication. Standard errors are clustered by applicant.

Finally note that this exercise holds program attributes, cutoffs, and the broader allocation environment fixed, and does not incorporate equilibrium responses through changes in application portfolios.

Results

One-sided corrections of persistence beliefs substantially affect fitted rankings, while corrections for both programs have more modest effects (Table 7). Adjusting only the 1st-choice persistence belief lowers the fitted probability of ranking the current 1st choice above the 2nd by 14.1 percentage points, while adjusting only the 2nd-choice persistence belief raises it by 12.7 points. Adjusting persistence beliefs for both programs raises the fitted probability by 0.2 points. Adjusting take-up beliefs for both programs, and jointly

Table 7. Ranking Responses and Compensating Expected-Earnings Differentials among Marginal Applicants

		ΔRank (pp)			$\Delta \ln w$
	Coef.	1st choice	2nd choice	Both	Both
	(1)	(2)	(3)	(4)	(5)
A. Ranking index					
Completion if admitted, q	2.74				
	(0.21)				
Log expected earnings at age 45	0.85				
	(0.35)				
B. Belief adjustments					
Take-up		-2.8	-1.6	-4.5	0.28
		(0.2)	(0.1)	(0.3)	(0.10)
Persistence		-14.1	12.7	0.2	-0.01
		(0.8)	(0.7)	(0.2)	(0.01)
Joint adjustment		-16.0	11.9	-2.7	0.15
		(1.0)	(0.6)	(0.2)	(0.06)

Note: Conditional logit with 1,976 applicants, field indicators, and distance controls, weighted by Abadie kappa times survey sampling weights. The take-up adjustment is estimated for admission compliers and the persistence adjustment for admission-induced enrollees. Here $q = \varepsilon_{ik}(1)\chi_{ik}(1)$; earnings are conditional on completion. ΔRank is the average change in the fitted probability of ranking the current 1st choice above the 2nd, in percentage points. $\Delta \ln w$ is the common change in log expected 1st-choice earnings that restores the baseline average fitted probability after correcting both programs. The joint adjustment corrects take-up and persistence; admission beliefs do not enter this specification. Parentheses contain applicant-clustered bootstrap standard errors conditional on the estimated belief adjustments.

adjusting take-up and persistence, lower it modestly (4.5 and 2.7 points).[24]

These results mirror Table 4: completion errors are large for both programs, while the error in their first-minus-second difference is small. Note that this is not mechanical since completion beliefs enter the model multiplied by take-up beliefs, which differ between programs, and the persistence corrections themselves differ by program.

Offsetting the joint adjustment would require an increase of 0.15 log points (SE 0.06), about 16 percent, in expected 1st-choice earnings relative to the 2nd choice.

Among all applicants, one-sided persistence adjustments also produce larger fitted responses than adjustments to both programs (Appendix Table A25). The two-program responses differ in direction across the populations, however: among all applicants, adjusting persistence beliefs for both programs raises the fitted probability (4.1 percentage points), as does the joint adjustment (2.1 points). The near-zero effect of balanced persistence corrections is therefore specific to marginal applicants.

Balanced persistence adjustments have little effect on fitted rankings across control

[24]The joint-adjustment response need not equal the sum of the separate take-up and persistence responses because fitted probabilities are nonlinear in the adjusted beliefs.

sets, functional forms, and earnings horizons, while the compensating earnings differential is more sensitive to the specification. Adding field indicators and distance controls changes the joint-adjustment response only from -2.8 to -2.7 points (Appendix Table A22). In an expected-earnings specification using $q_{ik}w_{ik}$, the joint adjustment has an additive earnings equivalent of NOK 57,300 (Appendix Table A23). With expected first-job earnings, the ranking responses are similar, but the earnings equivalent of the joint adjustment is larger (0.24 log points; Appendix Table A24).

The admission-augmented specification in Appendix Table A23 adds the elicited admission beliefs to (12), using the 2nd-choice belief conditional on missing the 1st choice.[25] Conditional on completion beliefs, expected earnings, and the controls, the admission-belief coefficient is negative (-2.79, SE 0.21); the first-job earnings specification gives a similar estimate (-2.84, SE 0.23). Admission beliefs may capture perceived selectivity or other valued program attributes. In the age-45 specification, jointly adjusting take-up and persistence lowers the fitted probability by 2.2 points. Adjusting admission beliefs alone raises it by 6.1 points, while adjusting all three stages raises it by 4.6 points.[26]

8 Conclusion

Applicants rank programs before they know where they will be admitted, whether they will enroll, and whether they will finish. We asked applicants in Norway about each of these stages for their first two choices before admission decisions, and compared their answers with outcomes under both choices for applicants who just made or just missed their first choice.

Before they learn about admissions, applicants are somewhat too optimistic about being admitted and much too optimistic about finishing. Among marginal applicants, forecasts of enrollment if admitted are close to outcomes on average, but applicants overpredict take-up at their first choice and underpredict it at their second, exaggerating the enrollment difference between programs. They greatly overpredict their chances of finishing if admitted to either program, mainly their chances of finishing if they enroll. Persistence overprediction appears in every group we examine.

[25] We use the elicited conditional belief because the unconditional second-choice admission probability includes the probability of missing the first choice and therefore partly reflects the ranking we are trying to explain.

[26] We add a rank-specific adjustment to the admission belief and truncate to $[0,1]$. For marginal applicants, the benchmarks are $\hat{p}$ for the 1st choice and 1 for the conditional 2nd-choice belief. The latter uses the C2 approximation: applicants missing their 1st choice receive their 2nd choice, treating the small C0 share as negligible. Each adjustment is the benchmark minus the corresponding Abadie-weighted mean belief.

We find that small errors can add up, and large errors can partly offset, when applicants compare programs. The enrollment errors have opposite signs and add up in the difference between programs. The completion errors have the same sign, and they partly cancel in the difference between programs. Where errors appear to arise also depends on how a forecast is conditioned. Most of the apparent underprediction of second-choice enrollment disappears when forecasts are conditioned on missing the first choice. Diagnosing belief errors therefore requires comparing beliefs with outcomes at each stage, for each alternative, and under the same conditions.

In the fitted ranking model, correcting beliefs about finishing for one program shifts rankings much more than correcting them for both. This holds for both marginal applicants and the broader applicant sample. Large forecast errors can therefore have modest ranking implications when they are shared across programs, while correcting only one program can change their perceived difference substantially.

Information interventions should therefore not only provide accurate information, but they should also be careful to target the relevant outcomes and choice margins.

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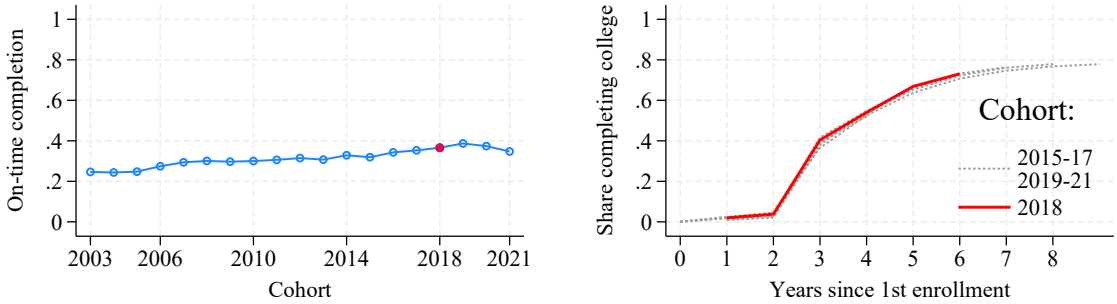
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Web Appendix with Supplementary Material

A Extra Figures

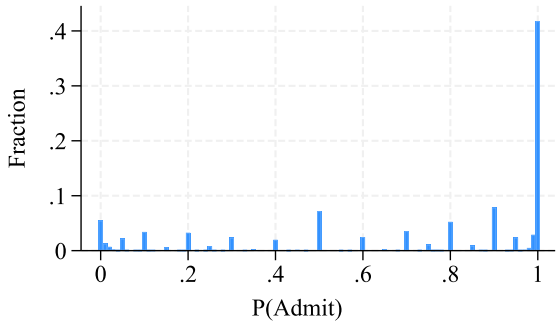


(a) On-time completion, 2003-2021 cohorts

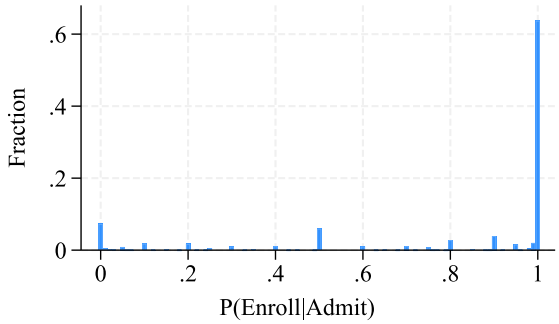
(b) Completion by year since 1st enrollment, 2015-2021 cohorts

Figure A1. Across cohort comparison of college completion

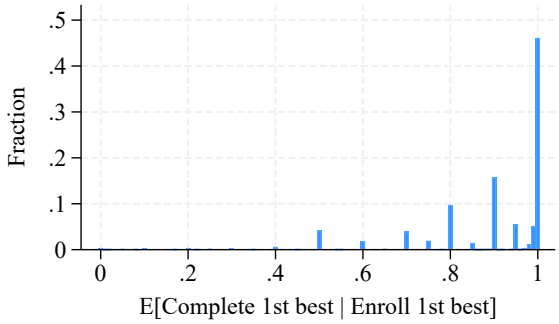
Note: Population register data. Completion is the first recorded college completion, irrespective of program. On-time completion denotes completion three calendar years after first enrollment; panel (b) reports cumulative completion.



(a) Admission belief



(b) Enrollment belief if admitted



(c) Completion belief if enrolled

Figure A2. Survey-Elicited Probabilities of Admission, Enrollment, and Completion in 1st Choice Program

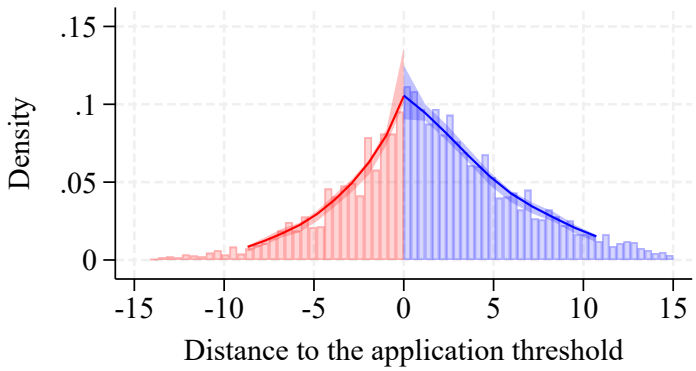
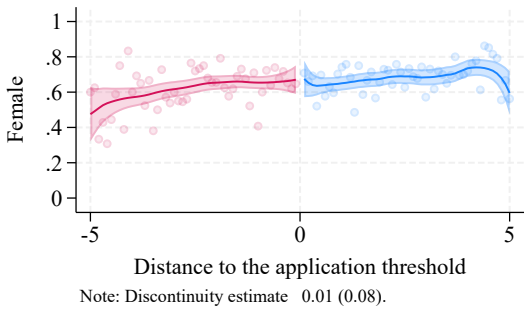
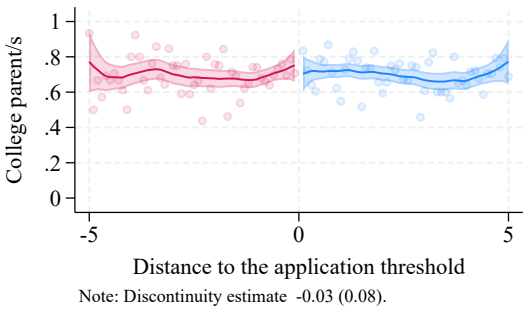


Figure A3. Bunching Test for Manipulation around the Admission Margin

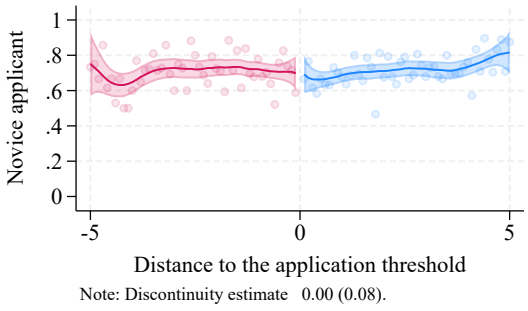
Note: The sample includes applicants at or above their 2nd-choice cutoff, including those exactly at the 1st-choice cutoff. Lines are local-polynomial density estimates with 95% confidence bands; bars show the observed density. The reported p-value tests continuity of the density at zero.



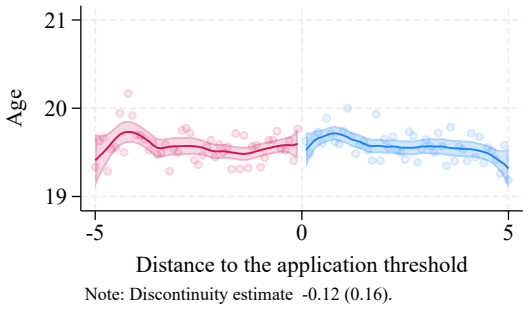
(a) Gender



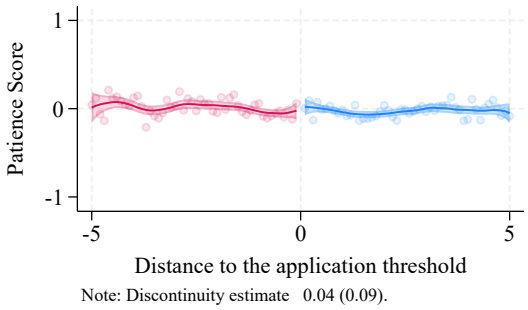
(b) Parental education



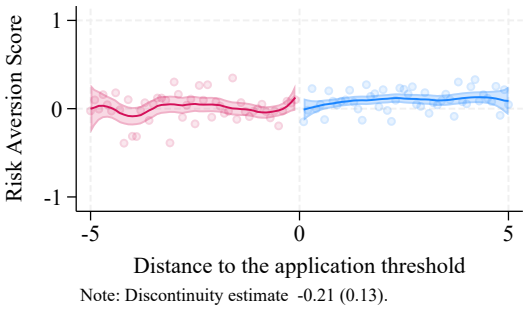
(c) Application experience



(d) Age



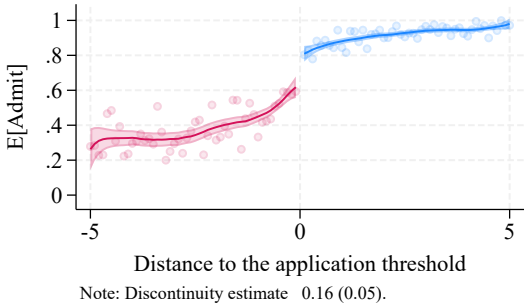
(e) Impatience



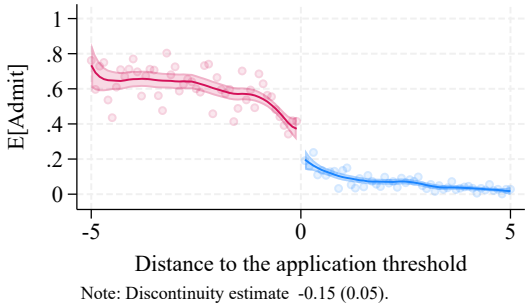
(f) Risk aversion/low competitiveness

Figure A4. Balancing of Predetermined Characteristics

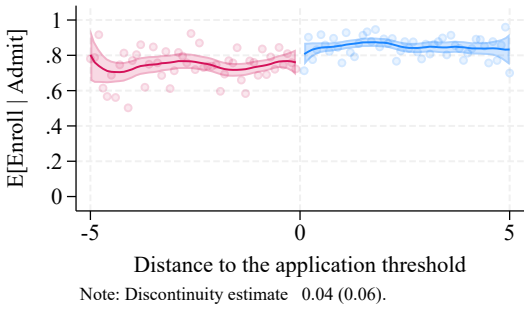
Note: Dots are unweighted means at each recorded distance from the 1st-choice cutoff. Curves are local-linear fits with pointwise 95% confidence bands. The sample is within five points of that cutoff and at or above the 2nd-choice cutoff; observations exactly at the 1st-choice cutoff are excluded. Panel notes report `rdhonest` discontinuity estimates and standard errors.



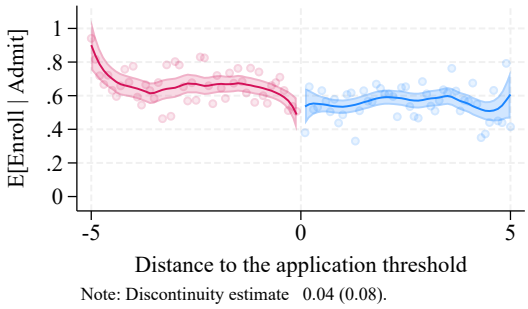
(a) Admission belief, first choice



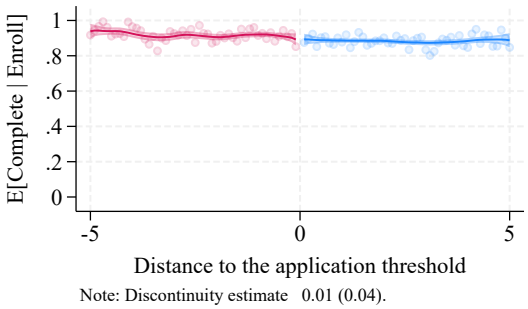
(b) Admission belief, second choice



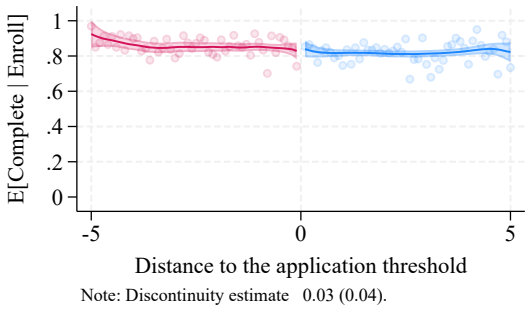
(c) Enrollment belief if admitted, first choice



(d) Enrollment belief if admitted, second choice



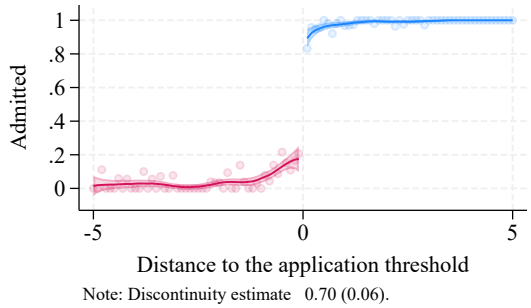
(e) Completion belief if enrolled, first choice



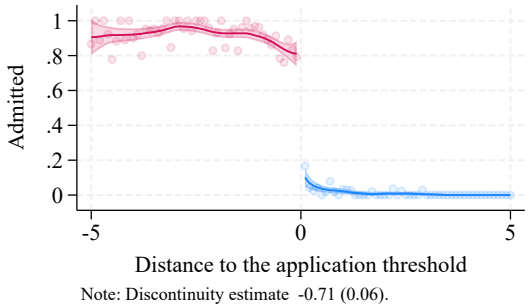
(f) Completion belief if enrolled, second choice

Figure A5. Balancing of Subjective Expectations (predetermined)

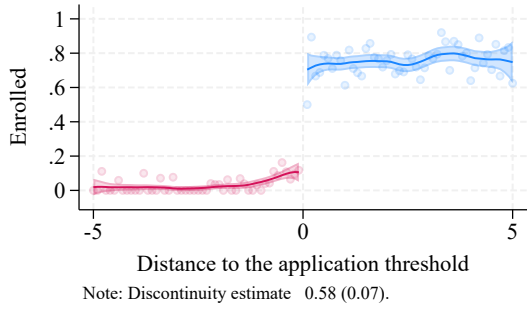
Note: Sample and plotting conventions are as in Figure A4. Distance is recorded in 0.1-point increments. Including observations exactly at the cutoff and controlling for distance indicators and program-pair fixed effects, the adjacent increases in 1st-choice admission beliefs are 0.100 from -0.1 to zero ($p = 0.324$) and 0.084 from zero to 0.1 ($p = 0.434$); their difference is -0.017 ($p = 0.921$). These comparisons do not distinguish a discontinuity from steep local curvature.



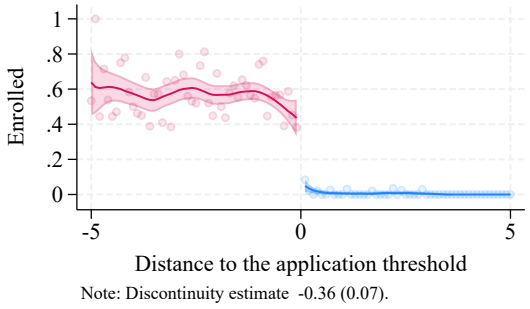
(a) Admission, first choice



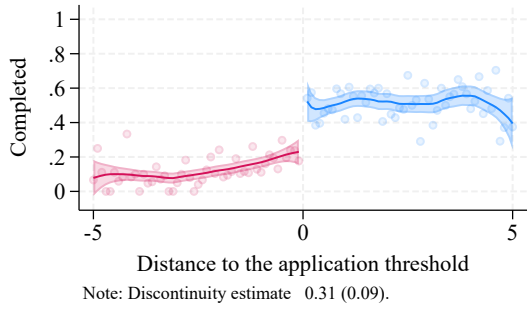
(b) Admission, second choice



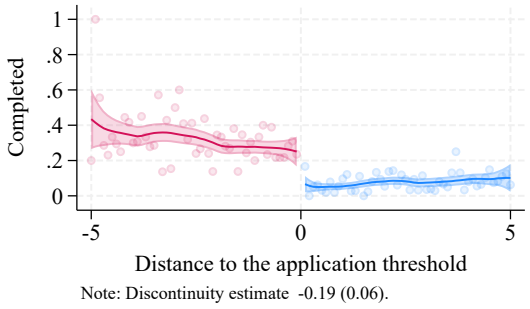
(c) Enrollment, first choice



(d) Enrollment, second choice



(e) Completion, first choice



(f) Completion, second choice

Figure A6. Admission, Enrollment, and Completion Discontinuities (Actual)
Note: Sample and plotting conventions are as in Figure A4. Outcomes are unconditional admission, August enrollment, and program-completion indicators. Completion is observed through 2024.

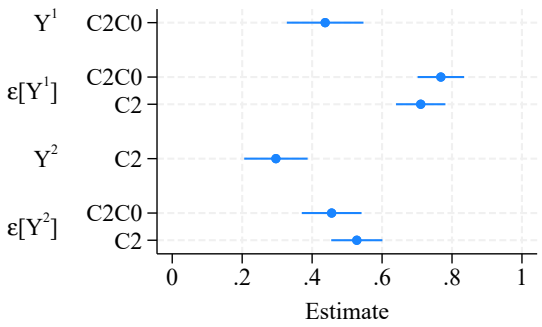


Figure A7. Objective and Subjective Completion if Admitted among Marginal Applicants

Note: Points are quadratic 2SLS estimates on the balanced sample in Table A6; bars are 95% confidence intervals.

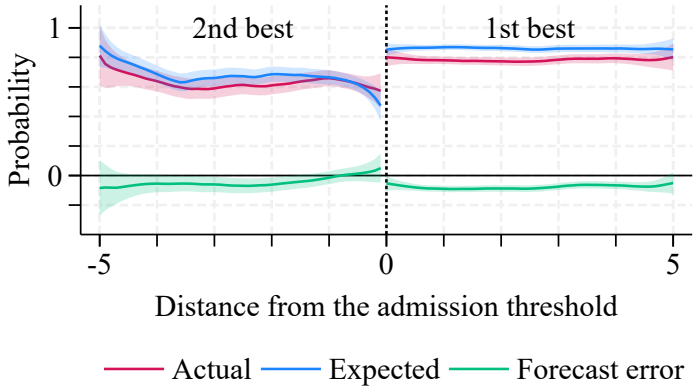


Figure A8. Enrollment If Admitted: Actual, Expected, and Forecast Error by Distance from the Admission Margin

Note: Curves are sampling-weighted local-linear means among admitted applicants: applicants admitted to their 2nd choice below the 1st-choice cutoff and to their 1st choice above it. Within each choice, all curves use the same observations with nonmissing outcomes and beliefs. Shading shows pointwise 95% confidence intervals. Actual enrollment is formal registration in August; forecast errors are actual minus expected.

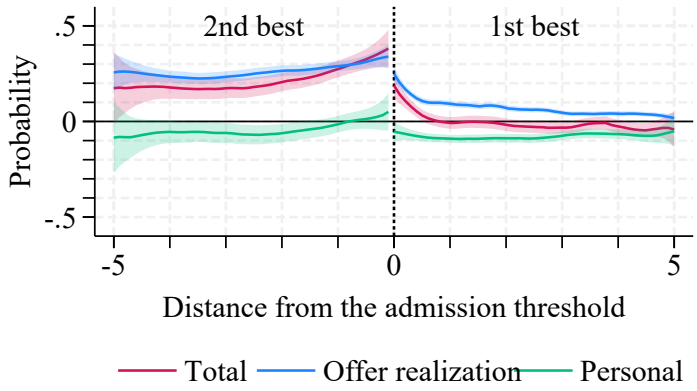


Figure A9. Enrollment Forecast Error: Decomposition into Personal (enrollment if admitted) and Admission Realization Components by Distance from the Admission Margin – All Treated

Note: Sample and plotting conventions are as in Figure A8. Components follow Eq. (4). Negative forecast errors indicate overprediction.

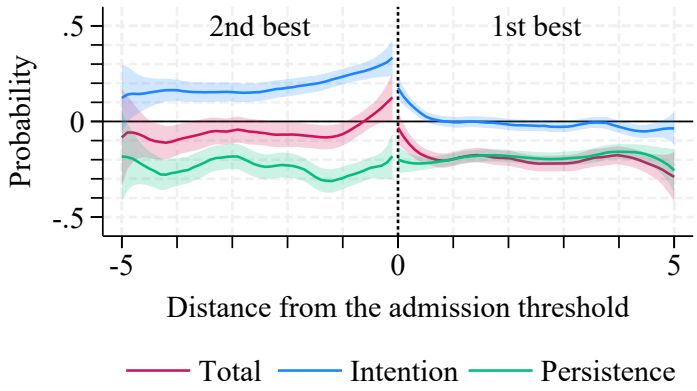


Figure A10. Completion Forecast Error: Decomposition into Intention (Enroll) and Persistence (completion if enrolled) Components by Distance from the Admission Margin – All Treated

Note: Sample and plotting conventions are as in Figure A8. Components follow Eq. (6), with completion observed through 2024. Negative forecast errors indicate overprediction.

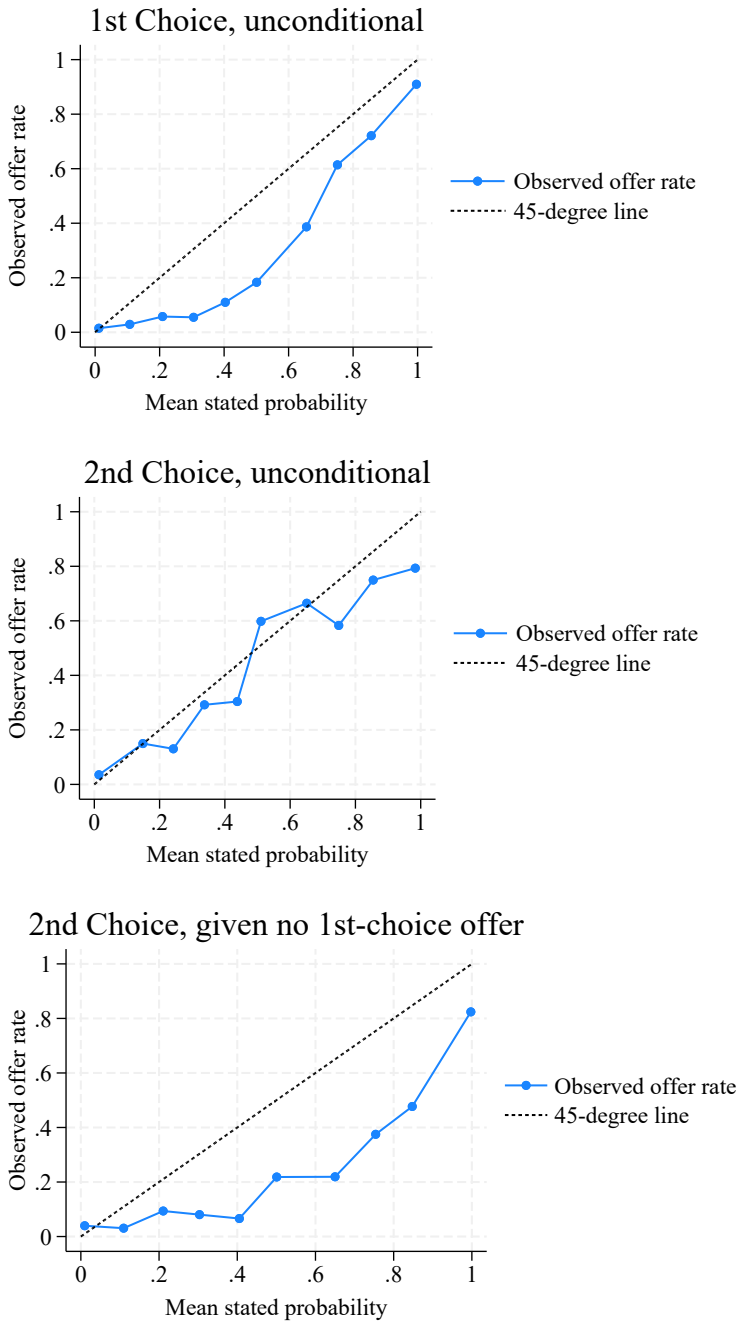


Figure A11. Calibration of Admission Beliefs: Realized Admission Rates by Stated Probability

Note: Points are sampling-weighted mean admission rates plotted against mean beliefs within ten-percentage-point belief bins. The final bin includes a stated probability of one.

B Extra Tables

Table A1. Analytic Sample Flow

Stage	Applicants	Weighted *N*
A. Baseline sample construction		
Linked and reshaped survey applicants	10,389	26,911.3
Observed 1st- and 2nd-choice programs	10,011	25,850.0
GPA-based admission programs	9,928	25,620.0
Within 25 points of the 1st-choice cutoff	9,133	23,611.3
Programs represented on both cutoff sides	8,855	22,886.0
Complete staged beliefs for the 1st choice	7,469	19,322.0
B. Analysis-specific samples		
At or above the 2nd-choice cutoff	3,998	10,230.7
Local 1st-choice-cutoff sample	2,746	7,014.7
Balanced principal-strata sample	2,142	5,437.3
Local sample with complete staged beliefs	2,144	5,442.7
All treated, 1st-choice admission	3,365	8,662.0
All treated, 2nd-choice admission	1,466	3,761.3
All-applicant ranking sample	5,902	15,192.0

Note: Panel A applies restrictions successively. Its first row includes linked partial responses; complete staged beliefs are imposed in its final row. Panel B reports analysis-specific samples. Weighted N sums inverse survey-sampling probabilities. Ranking samples are shown before requiring positive observed earnings for both programs; final estimation counts appear in Tables 7 and A25.

Table A2. Accuracy, Calibration, and Predictability of Admission Beliefs

A. Mean accuracy

Admission measure	N	Realized	Belief	Mean FE	p-value
1st-choice admission	7,469	0.448	0.568	-0.120	<0.001
				(0.004)	
2nd-choice admission, unconditional	5,903	0.209	0.226	-0.017	<0.001
				(0.004)	
2nd-choice fallback	3,430	0.358	0.521	-0.163	<0.001
				(0.006)	

B. Mincer-Zarnowitz calibration

Admission measure	α	β	Joint F	p-value
1st-choice admission	-0.09	0.95	$F(2,7467) = 520.23$	<0.001
2nd-choice admission, unconditional	0.02	0.84	$F(2,5901) = 45.99$	<0.001
2nd-choice fallback	-0.06	0.79	$F(2,3428) = 343.61$	<0.001

C. Predictability of forecast errors

Admission measure	N	Absorbed program effects	Joint F	p-value
1st-choice admission	7,148	1st-choice program	$F(6,6713) = 121.25$	<0.001
2nd-choice admission, unconditional	5,644	1st- and 2nd-choice programs	$F(8,4406) = 13.03$	<0.001
2nd-choice fallback	3,229	1st- and 2nd-choice programs	$F(8,2217) = 6.27$	<0.001

Note: Forecast errors are admission indicators minus stated probabilities. All estimates use survey sampling weights. Panels A and B use the same sample for each admission measure; Panel A reports robust standard errors and tests zero mean error. Panel B jointly tests intercept $\alpha = 0$ and slope $\beta = 1$. Panel C tests zero coefficients on GPA, previous-cutoff distances, and background characteristics, excluding the intercept and absorbed program effects. Fallback comparisons condition on no 1st-choice admission.

Table A3. Admission Statistics

	All applicants (1)	Conditional on any admission (2)	Conditional on non-1st-choice admission (3)
Admission outcome (%)			
1st choice	44.8	49.9	-
2nd choice	19.5	21.7	43.2
> 2nd choice	25.5	28.4	56.8
No program	10.2	-	-
N	7,469	6,742	3,377

Note: Admission is recorded as the highest-ranked offer received, so the admission categories are mutually exclusive.

Table A4. Discontinuity Tests around the Admission Margin

	Estimate (1)	SE (2)	*p*-value (3)
A. Background characteristics			
Female	0.01	0.08	0.891
At least one college-educated parent	-0.03	0.08	0.681
Age	-0.12	0.16	0.477
First-time applicant	0.00	0.08	0.988
Application score	-0.39	1.49	0.794
Impatience score	0.04	0.09	0.677
Risk-aversion/low-competitiveness score	-0.21	0.13	0.105
B. 1st-choice beliefs			
Admission probability	0.16	0.05	0.001
Enroll-if-admitted probability	0.04	0.06	0.522
Complete-if-enrolled probability	0.01	0.04	0.822

Note: Discontinuity estimates from `rdhonest`, using the unweighted sample described in Figure A4. P-values use the estimate divided by its standard error and a standard normal reference distribution.

Table A5. Applicants' Characteristics by Group: Marginal (Compliers), All Treated, and All Applicants

	Marginal applicants		All treated	All applicants
	(1)	(2)	(3)	(4)
Female	0.53	0.53	0.68	0.67
	(0.05)	(0.06)	(0.01)	
Age	19.9	19.5	19.8	19.8
	(0.09)	(0.26)	(0.02)	
First-time applicant	0.57	0.59	0.63	0.61
	(0.06)	(0.07)	(0.01)	
At least one college-educated parent	0.79	0.74	0.70	0.66
	(0.05)	(0.06)	(0.01)	
Application score	49.4	49.8	49.6	46.5
	(0.73)	(1.32)	(0.13)	
Risk-aversion/low-competitiveness score	-0.01	0.02	0.09	0
	(0.06)	(0.05)	(0.01)	
Impatience score	0.03	-0.01	-0.02	0
	(0.05)	(0.03)	(0.01)	
Field of study				
Social sciences and humanities	0.21	0.20	0.17	0.18
	(0.04)	(0.03)	(0.01)	
Science and engineering	0.28	0.26	0.23	0.20
	(0.05)	(0.04)	(0.01)	
Law and business	0.24	0.25	0.17	0.16
	(0.04)	(0.04)	(0.01)	
Teaching	0.06	0.06	0.12	0.09
	(0.03)	(0.02)	(0.01)	
Health	0.21	0.22	0.32	0.36
	(0.06)	(0.06)	(0.01)	
Estimator	2SLS	Local linear	Mean	Mean
N	2,315		2,789	7,469

Note: Columns (1)–(3) use the common sample with nonmissing listed characteristics and the estimators and survey weights described in Table 5, for 1st-choice admission. Column (4) reports survey-sampling-weighted means for all applicants. Parentheses contain standard errors. The factor scores are normalized as in Table 1.

Table A6. Potential Outcomes for 1st- and 2nd-Choice Programs among Marginal Applicants: Completion if admitted

	Stratum share	y^1	$\mathscr{E}[y^1]$	y^2	$\mathscr{E}[y^2]$
A. Unbalanced sample					
C2C0	0.78	0.47	0.78		0.46
	(0.02)	(0.05)	(0.03)		(0.04)
C2	0.76		0.70	0.29	0.53
	(0.02)		(0.03)	(0.04)	(0.04)
C0	0.02		0.47		0.24
	(0.01)		(0.32)		(0.25)
A1	0.17	0.60	0.83		0.49
	(0.01)	(0.04)	(0.02)		(0.03)
A2	0.05		0.46	0.04	0.41
	(0.01)		(0.05)	(0.06)	(0.06)
N	2,746	2,746	2,746	2,741	2,144
B. Balanced sample					
C2C0	0.79	0.44	0.77		0.46
	(0.02)	(0.06)	(0.03)		(0.04)
C2	0.77		0.71	0.30	0.53
	(0.02)		(0.04)	(0.05)	(0.04)
C0	0.02		0.51		0.24
	(0.02)		(0.27)		(0.24)
A1	0.15	0.59	0.80		0.49
	(0.01)	(0.04)	(0.02)		(0.03)
A2	0.05		0.30	0.06	0.41
	(0.01)		(0.06)	(0.07)	(0.06)
N	2,142	2,142	2,142	2,142	2,142

Note: Sampling-weighted quadratic 2SLS estimates with conventional standard errors in parentheses. Panel A uses available observations for each comparison; Panel B uses a common complete-case sample for the displayed outcomes and beliefs.

Table A7. Enrollment If Admitted: Actual, Expected, and Forecast Error

	Marginal applicants		All treated
	(1)	(2)	(3)
A. 1st-choice program			
(a) Actual ($e_{i1}(1)$)	0.80	0.81	0.78
	(0.042)	(0.049)	(0.007)
(b) Expected ($\varepsilon_{i1}(1)$)	0.86	0.84	0.86
	(0.028)	(0.036)	(0.005)
(c) Forecast error ($FE_{i1}^{e\|o}$)	-0.07	-0.06	-0.08
	(0.033)	(0.029)	(0.005)
N	2,746		3,365
B. 2nd-choice program			
(a) Actual ($e_{i2}(1)$)	0.67	0.64	0.63
	(0.052)	(0.040)	(0.014)
(b) Expected ($\varepsilon_{i2}(1)$)	0.60	0.52	0.66
	(0.042)	(0.048)	(0.011)
(c) Forecast error ($FE_{i2}^{e\|o}$)	0.07	0.07	-0.03
	(0.047)	(0.051)	(0.013)
N	2,144		1,245
Estimator	2SLS	`rdhonest`	Mean

Note: Enrollment is formal registration in August. Forecast error is actual minus expected. Column (1) uses local quadratic 2SLS; column (2) uses bias-aware local-linear `rdhonest` estimates with MSE-optimal bandwidths (Kolesár and Rothe, 2018); column (3) reports means among applicants admitted to the indicated program. Estimates use survey sampling weights and available observations for each column; Table 4 uses common complete-case samples. Standard errors are in parentheses.

Table A8. Mean Squared Error Decomposition for Unconditional Enrollment Forecasts

	Marginal applicants		All treated
	2SLS MSE (1)	Local linear MSE (2)	Mean MSE (3)
A. 1st-choice program			
(a) Admission realization	0.03	0.02	0.03
(b) Personal	0.08	0.07	0.10
Cross term	-0.00	-0.01	-0.02
(c) Total forecast error	0.10	0.08	0.11
N	2,746		3,365
B. 2nd-choice program			
(a) Admission realization	0.20	0.19	0.14
(b) Personal	0.22	0.21	0.21
Cross term	-0.04	-0.04	-0.07
(c) Total forecast error	0.38	0.36	0.28
N	2,144		1,245

Note: The component entries are mean squares of the weighted contributions defined in Eq. (4), not of the underlying stage errors. The cross term is $2\mathbb{E}[(a)(b)]$, and total MSE is the mean squared realized forecast error. Column (1) uses local quadratic 2SLS; column (2) uses local-linear `rdhonest` estimates with MSE-optimal bandwidths (Kolesár and Rothe, 2018). Column (3) reports means among applicants admitted to the indicated program. Estimates use survey sampling weights.

Table A9. Mean Squared Error Decomposition for Unconditional Completion Forecasts

	Marginal applicants		All treated
	2SLS MSE (1)	Local linear MSE (2)	Mean MSE (3)
A. 1st-choice program			
(a) Intention	0.07	0.06	0.09
(b) Persistence	0.30	0.30	0.24
Cross term	-0.08	-0.08	-0.05
(c) Total forecast error	0.30	0.30	0.28
N	2,746		3,364
B. 2nd-choice program			
(a) Intention	0.28	0.27	0.21
(b) Persistence	0.29	0.28	0.27
Cross term	-0.30	-0.28	-0.23
(c) Total forecast error	0.27	0.23	0.25
N	2,142		1,244

Note: The component entries are mean squares of the weighted contributions defined in Eq. (6), not of the underlying stage errors. The cross term is $2\mathbb{E}[(a)(b)]$, and total MSE is the mean squared realized forecast error. Column (1) uses local quadratic 2SLS; column (2) uses local-linear `rdhonest` estimates with MSE-optimal bandwidths (Kolesár and Rothe, 2018). Column (3) reports means among applicants admitted to the indicated program. Estimates use survey sampling weights.

Table A10. Enrollment Forecast Error: Decomposition by Gender

	All treated			Marginal applicants		
	Female (1)	Male (2)	Gap (1−2) (3)	Female (4)	Male (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Admission realization	0.076	0.067	0.010	0.096	0.084	0.013
	(0.003)	(0.005)	(0.006)	(0.029)	(0.028)	(0.040)
(b) Personal	-0.068	-0.102	0.034	-0.061	-0.070	0.010
	(0.006)	(0.010)	(0.012)	(0.042)	(0.055)	(0.069)
(c) Total forecast error	0.009	-0.035	0.044	0.036	0.013	0.022
	(0.007)	(0.012)	(0.013)	(0.044)	(0.061)	(0.075)
B. 2nd-choice program						
(a) Admission realization	0.250	0.270	-0.019	0.298	0.414	-0.115
	(0.010)	(0.014)	(0.017)	(0.036)	(0.050)	(0.062)
(b) Personal	-0.023	-0.045	0.022	0.064	0.080	-0.016
	(0.017)	(0.021)	(0.027)	(0.062)	(0.069)	(0.093)
(c) Total forecast error	0.227	0.224	0.003	0.362	0.494	-0.131
	(0.017)	(0.023)	(0.029)	(0.063)	(0.073)	(0.096)

Note: Components, groups of admitted applicants, and weights are as in Table 5. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A11. Completion Forecast Error: Decomposition by Gender

	All treated			Marginal applicants		
	Female (1)	Male (2)	Gap (1−2) (3)	Female (4)	Male (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Intention	0.009	-0.035	0.044	0.030	0.017	0.013
	(0.006)	(0.010)	(0.012)	(0.041)	(0.053)	(0.067)
(b) Persistence	-0.195	-0.189	-0.006	-0.252	-0.286	0.034
	(0.010)	(0.015)	(0.018)	(0.060)	(0.075)	(0.096)
(c) Total forecast error	-0.186	-0.224	0.038	-0.222	-0.269	0.047
	(0.010)	(0.016)	(0.019)	(0.066)	(0.086)	(0.109)
B. 2nd-choice program						
(a) Intention	0.199	0.191	0.008	0.310	0.394	-0.084
	(0.015)	(0.020)	(0.025)	(0.054)	(0.067)	(0.086)
(b) Persistence	-0.242	-0.268	0.026	-0.279	-0.269	-0.010
	(0.017)	(0.022)	(0.028)	(0.060)	(0.077)	(0.097)
(c) Total forecast error	-0.043	-0.077	0.034	0.031	0.125	-0.094
	(0.019)	(0.024)	(0.031)	(0.064)	(0.082)	(0.104)

Note: Components, groups of admitted applicants, and weights are as in Table 6. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A12. Enrollment Forecast Error: Decomposition by Parental Education

	All treated			Marginal applicants		
	College (1)	No college (2)	Gap (1−2) (3)	College (4)	No college (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Admission realization	0.067	0.089	-0.022	0.070	0.148	-0.078
	(0.003)	(0.005)	(0.006)	(0.023)	(0.044)	(0.050)
(b) Personal	-0.085	-0.063	-0.022	-0.075	-0.042	-0.033
	(0.006)	(0.009)	(0.011)	(0.039)	(0.064)	(0.075)
(c) Total forecast error	-0.018	0.025	-0.044	-0.005	0.106	-0.111
	(0.007)	(0.010)	(0.013)	(0.043)	(0.065)	(0.078)
B. 2nd-choice program						
(a) Admission realization	0.237	0.306	-0.069	0.328	0.378	-0.050
	(0.009)	(0.015)	(0.018)	(0.035)	(0.053)	(0.064)
(b) Personal	-0.037	-0.018	-0.020	0.049	0.131	-0.082
	(0.016)	(0.023)	(0.028)	(0.056)	(0.087)	(0.103)
(c) Total forecast error	0.200	0.289	-0.089	0.377	0.509	-0.132
	(0.016)	(0.026)	(0.030)	(0.056)	(0.098)	(0.113)

Note: College denotes at least one college-educated parent. Components, groups of admitted applicants, and weights are as in Table 5. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A13. Completion Forecast Error: Decomposition by Parental Education

	All treated			Marginal applicants		
	College (1)	No college (2)	Gap (1−2) (3)	College (4)	No college (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Intention	-0.017	0.023	-0.040	-0.003	0.095	-0.098
	(0.006)	(0.010)	(0.011)	(0.038)	(0.060)	(0.072)
(b) Persistence	-0.200	-0.178	-0.022	-0.228	-0.360	0.132
	(0.010)	(0.014)	(0.017)	(0.055)	(0.091)	(0.106)
(c) Total forecast error	-0.217	-0.155	-0.063	-0.230	-0.265	0.035
	(0.010)	(0.016)	(0.019)	(0.062)	(0.100)	(0.118)
B. 2nd-choice program						
(a) Intention	0.168	0.261	-0.093	0.308	0.431	-0.123
	(0.014)	(0.023)	(0.027)	(0.049)	(0.088)	(0.100)
(b) Persistence	-0.247	-0.262	0.015	-0.307	-0.177	-0.129
	(0.016)	(0.026)	(0.030)	(0.056)	(0.087)	(0.103)
(c) Total forecast error	-0.079	-0.001	-0.078	0.001	0.253	-0.252
	(0.017)	(0.028)	(0.033)	(0.059)	(0.097)	(0.114)

Note: College denotes at least one college-educated parent. Components, groups of admitted applicants, and weights are as in Table 6. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A14. Enrollment Forecast Error: Decomposition by Application Experience

	All treated			Marginal applicants		
	Novice (1)	Experienced (2)	Gap (1−2) (3)	Novice (4)	Experienced (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Admission realization	0.074	0.073	0.000	0.093	0.087	0.006
	(0.003)	(0.005)	(0.006)	(0.021)	(0.041)	(0.046)
(b) Personal	-0.093	-0.053	-0.040	-0.105	-0.018	-0.087
	(0.006)	(0.009)	(0.011)	(0.042)	(0.054)	(0.069)
(c) Total forecast error	-0.019	0.020	-0.040	-0.013	0.068	-0.081
	(0.007)	(0.010)	(0.012)	(0.046)	(0.058)	(0.074)
B. 2nd-choice program						
(a) Admission realization	0.257	0.259	-0.002	0.374	0.290	0.084
	(0.009)	(0.015)	(0.017)	(0.036)	(0.051)	(0.062)
(b) Personal	-0.054	0.007	-0.062	0.033	0.122	-0.088
	(0.016)	(0.023)	(0.028)	(0.058)	(0.077)	(0.097)
(c) Total forecast error	0.202	0.266	-0.064	0.408	0.412	-0.004
	(0.016)	(0.025)	(0.030)	(0.060)	(0.081)	(0.101)

Note: Novice denotes a first-time applicant. Components, groups of admitted applicants, and weights are as in Table 5. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A15. Completion Forecast Error: Decomposition by Application Experience

	All treated			Marginal applicants		
	Novice (1)	Experienced (2)	Gap (1−2) (3)	Novice (4)	Experienced (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Intention	-0.018	0.018	-0.036	-0.009	0.059	-0.068
	(0.007)	(0.008)	(0.011)	(0.041)	(0.052)	(0.066)
(b) Persistence	-0.203	-0.177	-0.027	-0.212	-0.333	0.120
	(0.010)	(0.014)	(0.017)	(0.054)	(0.084)	(0.100)
(c) Total forecast error	-0.221	-0.159	-0.062	-0.221	-0.274	0.052
	(0.010)	(0.016)	(0.019)	(0.062)	(0.094)	(0.113)
B. 2nd-choice program						
(a) Intention	0.179	0.224	-0.045	0.341	0.333	0.007
	(0.015)	(0.022)	(0.026)	(0.054)	(0.069)	(0.088)
(b) Persistence	-0.247	-0.260	0.013	-0.230	-0.333	0.102
	(0.016)	(0.025)	(0.029)	(0.058)	(0.080)	(0.099)
(c) Total forecast error	-0.068	-0.036	-0.033	0.110	0.001	0.110
	(0.017)	(0.028)	(0.032)	(0.063)	(0.084)	(0.105)

Note: Novice denotes a first-time applicant. Components, groups of admitted applicants, and weights are as in Table 6. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A16. Enrollment Forecast Error: Decomposition by Application Score

	All treated			Marginal applicants		
	High (1)	Low (2)	Gap (1−2) (3)	High (4)	Low (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Admission realization	0.049	0.120	-0.071	0.074	0.115	-0.041
	(0.003)	(0.006)	(0.007)	(0.023)	(0.042)	(0.048)
(b) Personal	-0.085	-0.063	-0.022	-0.057	-0.116	0.060
	(0.006)	(0.009)	(0.011)	(0.043)	(0.051)	(0.067)
(c) Total forecast error	-0.037	0.057	-0.094	0.018	-0.001	0.018
	(0.007)	(0.010)	(0.013)	(0.046)	(0.058)	(0.074)
B. 2nd-choice program						
(a) Admission realization	0.229	0.287	-0.058	0.361	0.344	0.017
	(0.011)	(0.012)	(0.016)	(0.035)	(0.057)	(0.067)
(b) Personal	-0.066	-0.010	-0.057	0.078	0.069	0.008
	(0.018)	(0.021)	(0.027)	(0.058)	(0.083)	(0.102)
(c) Total forecast error	0.163	0.278	-0.115	0.438	0.414	0.025
	(0.019)	(0.021)	(0.028)	(0.058)	(0.091)	(0.108)

Note: High denotes an application score above 46.4. Components, groups of admitted applicants, and weights are as in Table 5. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A17. Completion Forecast Error: Decomposition by Application Score

	All treated			Marginal applicants		
	High (1)	Low (2)	Gap (1−2) (3)	High (4)	Low (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Intention	-0.035	0.055	-0.089	0.018	-0.010	0.028
	(0.006)	(0.009)	(0.011)	(0.041)	(0.053)	(0.067)
(b) Persistence	-0.176	-0.225	0.049	-0.232	-0.298	0.066
	(0.010)	(0.015)	(0.018)	(0.057)	(0.083)	(0.101)
(c) Total forecast error	-0.211	-0.170	-0.040	-0.214	-0.309	0.095
	(0.010)	(0.016)	(0.019)	(0.063)	(0.096)	(0.115)
B. 2nd-choice program						
(a) Intention	0.137	0.243	-0.106	0.351	0.372	-0.021
	(0.016)	(0.019)	(0.025)	(0.050)	(0.084)	(0.098)
(b) Persistence	-0.210	-0.276	0.066	-0.273	-0.304	0.032
	(0.018)	(0.020)	(0.027)	(0.055)	(0.090)	(0.106)
(c) Total forecast error	-0.073	-0.033	-0.040	0.079	0.068	0.011
	(0.020)	(0.022)	(0.030)	(0.057)	(0.103)	(0.118)

Note: High denotes an application score above 46.4. Components, groups of admitted applicants, and weights are as in Table 6. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A18. Enrollment Forecast Error: Decomposition by Patience

	All treated			Marginal applicants		
	High (1)	Low (2)	Gap (1−2) (3)	High (4)	Low (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Admission realization	0.073	0.078	-0.005	0.084	0.087	-0.003
	(0.004)	(0.005)	(0.006)	(0.033)	(0.033)	(0.047)
(b) Personal	-0.080	-0.078	-0.002	-0.006	-0.165	0.159
	(0.008)	(0.008)	(0.011)	(0.051)	(0.053)	(0.074)
(c) Total forecast error	-0.006	0.001	-0.007	0.078	-0.078	0.156
	(0.009)	(0.009)	(0.013)	(0.058)	(0.055)	(0.080)
B. 2nd-choice program						
(a) Admission realization	0.261	0.255	0.005	0.346	0.351	-0.005
	(0.012)	(0.012)	(0.017)	(0.045)	(0.046)	(0.065)
(b) Personal	-0.063	0.007	-0.070	0.014	0.153	-0.139
	(0.020)	(0.020)	(0.028)	(0.070)	(0.078)	(0.105)
(c) Total forecast error	0.198	0.263	-0.065	0.360	0.505	-0.144
	(0.020)	(0.021)	(0.029)	(0.072)	(0.079)	(0.107)

Note: High denotes greater patience, corresponding to a factor score below the sampling-weighted median. Components, groups of admitted applicants, and weights are as in Table 5. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A19. Completion Forecast Error: Decomposition by Patience

	All treated			Marginal applicants		
	High (1)	Low (2)	Gap (1−2) (3)	High (4)	Low (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Intention	-0.007	0.002	-0.009	0.080	-0.075	0.155
	(0.008)	(0.008)	(0.011)	(0.053)	(0.049)	(0.072)
(b) Persistence	-0.189	-0.193	0.004	-0.274	-0.276	0.002
	(0.012)	(0.012)	(0.017)	(0.072)	(0.072)	(0.101)
(c) Total forecast error	-0.197	-0.191	-0.005	-0.195	-0.351	0.157
	(0.013)	(0.013)	(0.019)	(0.084)	(0.082)	(0.117)
B. 2nd-choice program						
(a) Intention	0.170	0.227	-0.057	0.280	0.438	-0.158
	(0.018)	(0.019)	(0.026)	(0.063)	(0.070)	(0.095)
(b) Persistence	-0.265	-0.248	-0.017	-0.304	-0.325	0.021
	(0.020)	(0.021)	(0.029)	(0.071)	(0.077)	(0.105)
(c) Total forecast error	-0.095	-0.021	-0.074	-0.024	0.113	-0.138
	(0.021)	(0.024)	(0.032)	(0.067)	(0.090)	(0.113)

Note: High denotes greater patience, corresponding to a factor score below the sampling-weighted median. Components, groups of admitted applicants, and weights are as in Table 6. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A20. Enrollment Forecast Error: Decomposition by Risk Tolerance

	All treated			Marginal applicants		
	High (1)	Low (2)	Gap (1−2) (3)	High (4)	Low (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Admission realization	0.078	0.073	0.005	0.078	0.093	-0.016
	(0.005)	(0.004)	(0.006)	(0.031)	(0.034)	(0.046)
(b) Personal	-0.097	-0.064	-0.033	-0.072	-0.089	0.017
	(0.009)	(0.007)	(0.012)	(0.062)	(0.042)	(0.075)
(c) Total forecast error	-0.019	0.010	-0.028	0.006	0.005	0.001
	(0.010)	(0.008)	(0.013)	(0.058)	(0.054)	(0.079)
B. 2nd-choice program						
(a) Admission realization	0.262	0.254	0.008	0.317	0.379	-0.062
	(0.012)	(0.012)	(0.017)	(0.044)	(0.046)	(0.064)
(b) Personal	-0.047	-0.009	-0.038	0.069	0.072	-0.003
	(0.020)	(0.019)	(0.028)	(0.080)	(0.070)	(0.106)
(c) Total forecast error	0.215	0.245	-0.030	0.385	0.450	-0.065
	(0.021)	(0.021)	(0.029)	(0.076)	(0.076)	(0.107)

Note: High denotes greater risk tolerance, corresponding to a factor score below the sampling-weighted median. Components, groups of admitted applicants, and weights are as in Table 5. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A21. Completion Forecast Error: Decomposition by Risk Tolerance

	All treated			Marginal applicants		
	High (1)	Low (2)	Gap (1−2) (3)	High (4)	Low (5)	Gap (4−5) (6)
A. 1st-choice program						
(a) Intention	-0.015	0.007	-0.022	0.015	0.000	0.015
	(0.009)	(0.007)	(0.011)	(0.053)	(0.048)	(0.072)
(b) Persistence	-0.205	-0.180	-0.025	-0.313	-0.243	-0.070
	(0.013)	(0.012)	(0.017)	(0.075)	(0.068)	(0.101)
(c) Total forecast error	-0.220	-0.173	-0.047	-0.298	-0.243	-0.055
	(0.014)	(0.013)	(0.019)	(0.081)	(0.082)	(0.115)
B. 2nd-choice program						
(a) Intention	0.188	0.209	-0.021	0.316	0.372	-0.055
	(0.019)	(0.018)	(0.026)	(0.068)	(0.067)	(0.095)
(b) Persistence	-0.268	-0.245	-0.023	-0.256	-0.362	0.106
	(0.020)	(0.021)	(0.029)	(0.070)	(0.077)	(0.104)
(c) Total forecast error	-0.080	-0.036	-0.044	0.060	0.010	0.050
	(0.022)	(0.023)	(0.032)	(0.076)	(0.081)	(0.111)

Note: High denotes greater risk tolerance, corresponding to a factor score below the sampling-weighted median. Components, groups of admitted applicants, and weights are as in Table 6. Marginal-applicant subgroup coefficients are estimated jointly in an interacted quadratic 2SLS model. Gaps and their robust standard errors are obtained by reparameterizing the same model. Robust standard errors are in parentheses.

Table A22. Ranking Responses and Compensating Expected-Earnings Differentials across Control Specifications – Marginal Applicants

	Base		Field and distance	
	ΔRank (pp)	$\Delta \ln w$ (log units)	ΔRank (pp)	$\Delta \ln w$ (log units)
A. Ranking-index coefficients				
Completion if admitted, q	2.71		2.74	
	(0.20)		(0.21)	
Log expected earnings	0.88		0.85	
	(0.32)		(0.35)	
B. Corrections applied to both programs				
Take-up	-4.6	0.27	-4.5	0.28
	(0.3)	(0.10)	(0.3)	(0.10)
Persistence	0.2	-0.01	0.2	-0.01
	(0.1)	(0.01)	(0.2)	(0.01)
Joint adjustment	-2.8	0.15	-2.7	0.15
	(0.2)	(0.06)	(0.2)	(0.06)
N	1,976			

Note: Definitions, weights, and inference are as in Table 7. The base specification omits field indicators and distance controls.

Table A23. Ranking Responses and Compensating Expected-Earnings Differentials across Age-45 Earnings Specifications – Marginal Applicants

	Expected earnings		Separable		Admission augmented	
	ΔRank (pp)	ΔEarnings (NOK 1,000)	ΔRank (pp)	$\Delta \ln w$ (log units)	ΔRank (pp)	$\Delta \ln w$ (log units)
A. Ranking-index coefficients						
$q\times$ earnings		0.185				
		(0.056)				
Completion if admitted, q				2.74		3.75
				(0.21)		(0.25)
Log expected earnings				0.85		0.58
				(0.35)		(0.22)
Admission belief						-2.79
						(0.21)
B. Corrections applied to both programs						
Admission belief					6.1	-0.76
					(0.3)	(0.27)
Take-up	-2.6	62.7	-4.5	0.28	-4.8	0.55
	(0.6)	(1.7)	(0.3)	(0.10)	(0.2)	(0.20)
Persistence	-0.8	19.7	0.2	-0.01	0.8	-0.09
	(0.2)	(4.4)	(0.2)	(0.01)	(0.2)	(0.04)
Joint adjustment	-2.4	57.3	-2.7	0.15	-2.2	0.24
	(0.5)	(4.9)	(0.2)	(0.06)	(0.2)	(0.09)
All three stages					4.6	-0.52
					(0.4)	(0.19)
N				1,976		

Note: Definitions, weights, and inference are as in Table 7. All models include field indicators and distance controls. The expected-earnings model uses qw, with w in NOK 100,000; compensation is a common additive shift in 1st-choice qw, reported in NOK 1,000. The separable model uses q and $\log(w)$; the admission-augmented model also includes the admission belief, conditional on no 1st-choice admission for the 2nd choice. Their compensation is a common change in log 1st-choice earnings. The joint adjustment corrects take-up and persistence. The all-three-stages adjustment additionally corrects admission beliefs and is reported only for the admission-augmented model. Earnings are at age 45, conditional on completion.

Table A24. Ranking Responses and Compensating Expected-Earnings Differentials Using First-Job Earnings – Marginal Applicants

	Expected earnings		Separable		Admission augmented	
	ΔRank (pp)	ΔEarnings (NOK 1,000)	ΔRank (pp)	$\Delta \ln w$ (log units)	ΔRank (pp)	$\Delta \ln w$ (log units)
A. Ranking-index coefficients						
$q\times$ earnings	0.415					
	(0.092)					
Completion if admitted, q			2.81		3.81	
			(0.22)		(0.23)	
Log expected earnings			0.56		0.51	
			(0.18)		(0.14)	
Admission belief					-2.84	
					(0.23)	
B. Corrections applied to both programs						
Admission belief					6.2	-0.88
					(0.3)	(0.37)
Take-up	-3.3	37.5	-4.7	0.43	-4.9	0.63
	(0.6)	(0.8)	(0.3)	(0.15)	(0.2)	(0.27)
Persistence	-0.8	8.1	0.2	-0.02	0.8	-0.11
	(0.2)	(2.6)	(0.1)	(0.01)	(0.2)	(0.05)
Joint adjustment	-2.9	30.6	-2.8	0.24	-2.2	0.27
	(0.4)	(2.8)	(0.2)	(0.09)	(0.2)	(0.12)
All three stages					4.7	-0.61
					(0.5)	(0.27)
N	2,047					

Note: Specifications, definitions, weights, and inference are as in Table A23, using expected first-job earnings conditional on completion.

Table A25. Ranking Responses and Compensating Expected-Earnings Differentials – All Applicants

		ΔRank (pp)			$\Delta \ln w$
	Coef.	1st choice	2nd choice	Both	Both
	(1)	(2)	(3)	(4)	(5)
A. Ranking index					
Completion if admitted, q	2.84				
	(0.12)				
Log expected earnings at age 45	0.50				
	(0.10)				
B. Belief adjustments					
Take-up		-3.6	1.3	-2.2	0.23
		(0.1)	(0.0)	(0.1)	(0.05)
Persistence		-11.0	13.5	4.1	-0.40
		(0.4)	(0.4)	(0.2)	(0.08)
Joint adjustment		-13.6	14.1	2.1	-0.21
		(0.5)	(0.4)	(0.1)	(0.04)
N	5,389				

Note: The specification, response measures, and inference are as in Table 7, using survey sampling weights without kappa weights. Belief corrections are sampling-weighted objective-minus-subjective mean gaps among applicants who reach the relevant stage.

C Survey Instrument

In this appendix, we report the subset of questions from the survey instrument we use in the analysis.

1. Did you apply this year to higher education through NUCAS?
   (a) yes [continue to Block A]
   (b) no [continue to Block B]

Block A

In what follows we will ask you about your first and second choices in your application to NUCAS.

2. Can you tell us what your 1st and 2nd choices were in your application?
   (a) first choice
   (b) second choice

In what follows we will refer to (a) as your "first choice", and (b) as your "second choice"

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3. What do you think is the chance (%) that you will get an offer
   (a) for your first choice? ☐ %
   (a number from 0 to 100, where 0% is no chance and 100% is certain)
   (b) for your second choice (assuming you do not get an offer for your first choice)? ☐ %
   (a number from 0 to 100, where 0% is no chance and 100% is certain)
4. Suppose you get the offer, what is the chance (%) that you will enroll
   (a) in your first choice? ☐ %
   (a number from 0 to 100, where 0% is no chance and 100% is certain)
   (b) in your second choice? ☐ %
   (a number from 0 to 100, where 0% is no chance and 100% is certain)
5. Suppose you were to enroll there. What is the likelihood (in percent) that you will graduate from

(a) your first choice? ☐ %

(a number from 0 to 100, where 0% is no chance and 100% is certain)

(b) your second choice? ☐ %

(a number from 0 to 100, where 0% is no chance and 100% is certain)

6. Suppose you were to graduate from your **first choice**.

   (a) What do you expect to earn per year in your first job? (before taxes, in today's crowns)

   ☐ 000 NOK

7. Suppose you were to graduate from your **second choice**.

   (a) What do you expect to earn per year in your first job? (before taxes, in today's crowns) ☐ 000 NOK

8. Suppose you were to graduate from your **first choice**.

   (a) What do you expect to earn per year when you are 45? (before taxes, in today's crowns)

   ☐ 000 NOK

9. Suppose you were to graduate from your **second choice**.

   (a) What do you expect to earn per year when you are 45? (before taxes, in today's crowns) ☐ 000 NOK

10. Suppose you won't (and will never) get an offer for your first choice, but instead get offered your second choice.

    How much would you be prepared to pay to get an offer for your first choice? ☐ 000 NOK

[continue to Block C]

Block B

11. What is the chance (%) that you will apply for higher education through NUCAS at some later point?

    ☐ %

12. Have you applied or do you intend to apply for higher education (in Norway or abroad) not through NUCAS this year?

(a) yes

(b) no

[continue to Block C]

Block C

13. How well does the following statement describe you as a person?

    I abstain from things today so that I will be able to afford more tomorrow.

    Please use a scale from 0 to 10, where 0 means "does not describe me at all" and a 10 means "describes me perfectly". You can also use the values in-between to indicate where you fall on the scale.

0	1	2	3	4	5	6	7	8	9	10

14. How do you see yourself:

    As a person who is generally willing to take risks, or as someone who tries to avoid taking risks?

    Please use a scale from 0 to 10, where a 0 means you are "completely unwilling to take risks" and a 10 means you are "very willing to take risks". You can also use the values in-between to indicate where you fall on the scale.

0	1	2	3	4	5	6	7	8	9	10

15. *How competitive do you consider yourself to be?*

    Please use a scale from 0 to 10, where the value 0 means 'not competitive at all' and the value 10 means 'very competitive'. You can also use the values in-between to indicate where you fall on the scale.

0	1	2	3	4	5	6	7	8	9	10

Questions to be randomized:

16. Is there any program that you prefer to your first choice at NUCAS, but that you decided not to rank first there?

    If yes:

    (a) [specify program from list, as A1] []

(b) [if different from actual first choice] How much would you be prepared to pay to get an offer for this program instead of your listed first preference? (Suppose you can finance this through Lånekassen.)

[if different from actual first choice] ☐ 1000 NOK

17. Do you prefer [A] 1000 NOK today, or [B] 154*10=1540 NOK a year from now?

- if [A]
  (a) Do you prefer [A] 1000 NOK today, or [B] 185*10=1850 NOK a year from now?
    - etc
- if [B]
  (a) Do you prefer [A] 1000 NOK today, or [B] 125*10=1250 NOK a year from now?
    - etc

18. Do you prefer [A] 1000 NOK with certainty, or [B] a 50% chance of winning 154*20=3080 NOK?

- if [A]
  (a) Do you prefer [A] 1000 NOK with certainty, or [B] 50% chance of winning 185*20=3700 NOK?
    - etc
- if [B]
  (a) Do you prefer [A] 1000 NOK with certainty, or [B] 50% chance of winning 125*20=2500 NOK?
    - etc