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GETTING IN AND GETTING THROUGH: EX ANTE BELIEFS AND COUNTERFACTUAL OUTCOMES IN CENTRALIZED COLLEGE ADMISSIONS

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

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Abstract

We study belief accuracy in a centralized higher-education admissions system using Norwegian data that combine a large pre-admission expectations survey with administrative records on offers, enrollment, and completion. Program-specific cutoffs provide a fuzzy regression discontinuity design that identifies objective counterfactual outcomes at the admission margin and allows direct comparison with subjective, state-contingent beliefs (first-choice access versus the relevant second-choice offer state). We find that enrollment forecast errors are driven mainly by mistaken beliefs about offer probabilities, while beliefs about enrollment conditional on an offer are comparatively accurate. For completion, the dominant error is persistence optimism: applicants substantially overestimate completion conditional on enrollment under both access states. Applicants also overstate first-minus-second returns for both enrollment and completion. These errors are economically meaningful for choices: in a partial-equilibrium counterfactual exercise, correcting beliefs implies large declines in the predicted probability of keeping the currently ranked first choice on top.

JEL classification: C21, C83, D84, I26.

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1 Introduction

Centralized admissions systems allocate scarce seats in higher education for millions of applicants worldwide. These systems have attractive incentive properties, but outcomes are a function of the rankings applicants submit. Those rankings depend on what applicants expect admission offers to translate into. For applicants, the relevant object is not only getting in (admission), but also getting through (enrollment and completion) (e.g., Gandil 2025; Gandil and Leuven 2025).

Forming accurate beliefs about outcomes at the application stage is informationally demanding because it requires beliefs about at least three linked stages: (i) the probability of receiving an offer, (ii) the probability of enrolling if offered, and (iii) the probability of completing if they enroll. Forecast errors at any stage can distort submitted rankings and application portfolios (e.g., Agte et al. 2024; Larroucau et al. 2025). They can also affect how applicants and policymakers evaluate capacity expansions at oversubscribed programs (e.g., Tincani et al., 2025). This paper studies applicants' beliefs over the offer-enrollment-completion pipeline, how these beliefs compare to objective counterfactual outcomes at the admissions margin, where forecast errors enter, and the resulting implications for the rankings applicants submit.

Our contribution is to bring prospective, state-contingent beliefs and design-based identification together in a single setting, at scale. We fielded a large expectations survey in Norway shortly after higher-education applicants submitted their ranked lists but before they learned admission outcomes. We can link these survey responses to administrative records on offers, enrollment, and completion. The Norwegian higher-education admission system also generates program-specific cutoffs whose exact values are not known to applicants; near these cutoffs, offer status changes discontinuously, delivering a fuzzy regression discontinuity design for the causal effect of an offer, as in Kirkebøen et al. (2016). This setting lets us do three things that are rarely possible simultaneously.

First, we observe prospective, state-contingent beliefs over the full sequence from offers to completed schooling. In particular, we elicit applicants' subjective probabilities of enrolling if admitted and of completing if admitted and enrolled under access to their top-ranked program versus the highest-ranked program they would be offered if they were not offered their first choice. Differences in these state-contingent beliefs across access states are "*ex ante* returns," in the language of Arcidiacono et al. (2020), or "subjective *ex ante* treatment effects" (S*ea*TE), in the language of Giustinelli and Shapiro (2024).

Second, we can validate these beliefs against design-identified objective counterparts at the same admissions margin. On the objective side, we estimate the causal effects of offers on enrollment and completion using quasi-random variation in admission generated by the cutoffs.[1] Because we elicit beliefs under both access states and identify objective potential outcomes under both states at the cutoff margin, we can compare belief-implied and objective counterfactual levels—not only contrasts—for the same subpopulation at the margin of admission.

Third, we can locate where errors enter along the pipeline. We provide a potential outcomes framework that clarifies which subjective and objective objects are comparable for marginal applicants at a cutoff, and implementable decompositions that separate mistakes about admission probabilities (a system component) from mistakes about take-up conditional on an offer (a personal component), and separate mistakes about unconditional enrollment (an intention component) from mistakes about completion conditional on enrollment (a persistence component). This makes it possible to move beyond documenting average forecast errors to identifying which stage of the decision problem drives them.

Our main findings show large and policy-relevant forecast errors, concentrated in specific stages. Forecast errors in unconditional enrollment are driven primarily by inaccurate beliefs about admission probabilities, whereas enroll-if-admitted subjective probabilities are relatively close to realized take-up. In contrast, complete-if-enroll subjective probabilities are widely inaccurate and substantially overestimate persistence.[2] For instance, among applicants at the margin between their first-choice and second-choice offer states, the mean subjective probability of completing conditional on starting is 0.91 under first-choice access, while the corresponding design-based estimate of completion conditional on enrollment is approximately 0.53, and overestimation is similarly large under the second-choice offer state. The result is a large gap in expected versus realized completed schooling per offer. In addition to these errors in levels under each offer state, applicants are also not more accurate about returns: they overstate the first-minus-second return for both predicted enrollment and predicted completion.

These errors are socially patterned: applicants with stronger proxies for information (e.g., college-educated parent(s)) or achievement (e.g., above-median GPA) have more accurate (or less inaccurate) perceptions of admission chances and persistence, although not of their enrollment response conditional on admission.

Finally, we show that these forecast errors are consequential for applicants' portfolios. In a partial-equilibrium pairwise-choice exercise for the first- versus second-choice ranking, replacing subjective beliefs with corrected beliefs produces large changes in the predicted probability that applicants keep their current first choice ranked first. The estimated average reduction in the predicted probability of keeping the current first choice

[1] Related work on objective returns to admissions includes Hastings et al. (2013); Bechichi and Thebault (2021); Braccioli et al. (2023); Bertanha et al. (2024); Carlana et al. (2024); Gandil (2025); Cabrera-Hernandez et al. (2026), among others.

[2] See also Stinebrickner and Stinebrickner (2012, 2014a,b) and Giustinelli (2022) for a recent review.

ranked first is about 25 percentage points, and forecast errors in beliefs about persistence (completion conditional on enrollment) account for about 70 percent of the full-correction effect.

These results speak directly to a growing literature on how information frictions shape behavior in centralized assignment markets (see reviews by Rees-Jones and Shorrer (2023) and Che et al. (2025)). Even when assignment mechanisms are strategy-proof, participants still need accurate beliefs about assignment chances to search effectively, form application portfolios, and avoid non-placement or low-quality matches, and scalable "smart matching" information can improve outcomes (e.g., Arteaga et al. (2022), Larroucau et al. (2025)). Welfare comparisons between alternative assignment mechanisms can also hinge on belief accuracy: analyses that assume accurate beliefs may recommend the wrong design (e.g., Kapor et al. (2020)). We bring this perspective to higher-education admissions and, crucially, to beliefs not only about getting in but also about enrolling and then persisting through completion.

The joint measurement of subjective and objective returns is central because, as formally shown by Manski (1993) within a model of school-work decisions and wage outcomes, 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. But validating subjective treatment effects against objective ones is not automatic (e.g., Bernheim et al., 2024; Giustinelli and Shapiro, 2024).[3] Credible identification of objective effects requires a causal research design to address unobservability of counterfactual outcomes, and objective effects are typically identified for a specific margin and subpopulation. This makes it nontrivial to validate subjective counterfactual beliefs against the correct objective estimand in the correct subpopulation.[4]

A small but growing set of papers tackles this validation problem by combining elicited state-contingent beliefs and research designs that identify the corresponding objective counterfactuals at a well-defined margin. Briggs et al. (2024) connect subjective expectations to marginal treatment effects (MTE) of childbirth on maternal labor supply in Denmark and compare subjective and objective MTE objects identified using policy-induced variation. Attanasio et al. (2025) compare subjective and experimental causal objects in

[3] McKenzie (2018) and Parker and Souleles (2019) present early attempts based on ex post beliefs rather than ex ante ones.

[4] Empirical assessments of the accuracy of subjective beliefs or expectations about "simple" random variables against their realizations are commonplace in economics, given the longstanding tradition of testing "rational expectations" (e.g., Muth, 1961; Lovell, 1986; Pesaran and Weale, 2006; D'Haultfoeuille et al., 2021; Crossley et al., 2024). Analyses that isolate sources of belief errors when predicting sequential or joint outcomes are relatively less common; recent exceptions include Gong et al. (2019); Crossley et al. (2022); Gong et al. (2022); Caplin et al. (2025).

the context of maternal investments and child skill formation in Colombia. Our contribution is complementary: in a centralized admissions setting with cutoff-driven quasi-random assignment, we elicit beliefs for multiple stages of the admission-enrollment-completion pipeline and can compare belief-implied and design-identified counterfactual levels (and not only contrasts) for the same marginal applicants, then decompose where misperceptions arise and illustrate how they can distort application portfolios.

Our paper also contributes to the growing literature that uses survey expectations to measure subjective causal effects (e.g., Dominitz and Manski, 1996; Arcidiacono et al., 2020; Wiswall and Zafar, 2021; Hudomiet et al., 2021; Briggs et al., 2024; Giustinelli and Shapiro, 2024; Goncalves Raposo, 2024; Angelov et al., 2026; Meango and Girsberger, 2026).

Our results have immediate implications for the design of admissions systems and information policy. If the main mistake underlying enrollment prediction is misunderstanding admission chances, then applicants would benefit from information on personalized admission probabilities. If the main mistake underlying completion prediction is overestimating one's persistence after starting, then applicants would also need realistic, program-specific completion risks: not only to choose where to apply, but to form accurate expectations about what admission implies for completed schooling.

The remainder of the paper is organized as follows. Section 2 describes the institutional context of higher-education admissions in Norway and the identification strategy. Section 3 introduces objective and subjective returns within a potential outcomes framework and derives the decompositions of belief errors. Section 4 presents the survey and administrative data and describes the analytic sample. Section 5 discusses identification of treatment effects and counterfactual outcomes and describes the econometric implementation. Section 6 presents the main estimates of objective and subjective returns and counterfactuals defined in Sections 3 and 5. Section 7 uses the forecast-error decompositions from Section 3 to locate the main sources underlying the discrepancies between objective and subjective objects documented in Section 6, separating mistakes about (i) admission probabilities (system component) from mistakes about own take-up conditional on an offer (personal component), and (ii) mistakes about unconditional enrollment (intention component) from mistakes about completion once enrolled (persistence component). Section 8 translates these forecast errors into partial-equilibrium portfolio implications by examining how corrected beliefs would change the predicted ranking of applicants' first- versus second-choice programs. Section 9 concludes.

2 Institutional Context

The institutional context of our study is the process of application and admission to higher education in Norway.[5] The process operates through a centralized choice system, which uses a serial dictatorship mechanism with a common priority ranking[6] and covers nearly all universities and colleges in the country.[7] Kirkebøen et al. (2016) provide a detailed contemporary description of the system. In this subsection, we focus on the aspects that are most relevant to our analysis of objective and subjective returns to admission.

Institutions set planned study places subject to budget constraints and funding rules; the ministry and parliament periodically expand capacity in particular fields or programs, often by specifying expected increases in output.

The demand for programs is determined by the applications submitted by prospective students. During their last year of high school (or subsequently), qualified individuals can apply to higher education through the centralized online portal of the Norwegian Universities and Colleges Admission Service (NUCAS),[8] where 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.[9]

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.

Often demand exceeds supply in many programs, which are therefore constrained. In oversubscribed programs, admission is determined by a program-year score cutoff that emerges from capacity and demand and is not known with certainty when applicants submit preferences. Specifically, applicants are allocated to the available slots via a serial dictatorship mechanism with a common priority ranking, which is theoretically strategy-proof and Pareto efficient (Svensson, 1999).[10] In practice, university applicants are first ranked according to their application score, which is largely determined by the applicant's

[5]The Norwegian higher education sector includes the major public universities, located in Bergen, Oslo, Trondheim, and Tromsø, and a number of public and private university colleges, all of which are funded and regulated by the Ministry of Education and Research. The main public universities offer a wider selection of fields than the latter group, whose offerings are usually limited to professional degrees in fields such as engineering, health, business, and teaching. Most degree programs follow the 3-year bachelor and 2-year master structure, while some integrated professional programs are longer. There are generally no tuition fees for attending, and the vast majority of students attend public institutions and are eligible for financial support (part loan/part grant) from the Norwegian State Educational Loan Fund.

[6]It is therefore equivalent to a deferred acceptance mechanism.

[7]A notable exception is the Norwegian Business School in Oslo, which is not part of the system.

[8]Samordna Opptak (SO) in Norwegian; see https://www.samordnaopptak.no/info/.

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

[10]A potential threat to the strategy-proofness is the truncation of the application list at 10 programs. This truncation may induce applicants to list a safe option as their 10th choice.

high school GPA.[11] 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 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 offers are assigned to the waiting applicants through a second round of offers, generated using the same serial dictatorship mechanism as in the first round. 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.[12]

Around mid-August, students start higher education in their accepted program. Students who wish to change field or institution typically 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 constrained programs with excess demand, this system generates a setting whereby applicants with a score above a certain threshold are substantially more likely to be offered their first-choice program (or a higher-ranked program) than applicants with the exact same preferences over programs but a marginally lower application score. This, in turn, creates credible instruments from discontinuities that effectively randomize applicants near unknown admission cutoffs into different programs (field-institution pairs). Kirkebøen et al. (2016) provide more details and useful examples.

[11] In Norway, high school grades in individual subjects range from 1 to 6 (integer values only). A student's GPA is the average grade (up to two decimal places) multiplied by 10. University applicants can gain a few extra points by selecting specific subjects in high school, by applying to university programs in which they are underrepresented (e.g., female applicants applying to a male-dominated program), or due to specific personal characteristics or circumstances (e.g., age, previous education, and fulfillment of military service).

[12] Table A1 summarizes the outcome of this admission process in our sample (further described below). Nearly 90% of our applicants received an offer; 47% for their 1st choice program. Among those who receive an offer, over 50% of applicants received an offer for their 1st choice program; over 80% for a program among their top 3 choices. Conditional on not receiving an offer for their 1st choice, over 40% of our applicants received an offer for their 2nd choice and over 20% for their 3rd choice.

3 Analytic Framework

This section defines the objective and subjective estimands of interest, and introduces the forecast errors and decompositions that organize the empirical analysis. The belief objects are elicited after applicants submit ranked lists but before admission offers are issued. Throughout, we focus on applicants' first-choice and second-choice programs ($k = 1, 2$). The role of the research design is to map these belief objects to the corresponding objective potential outcomes at the same local admissions margin; identification and estimation are discussed in Section 5.

3.1 Objective and Subjective Causal Effects: Enrollment 'Returns' to Admission

Objective effects Let $o_{ik} \in \{0,1\}$ indicate whether applicant i is offered a slot in her kth priority program, with $o_{ik} = 1$ denoting an offer (admission) and $o_{ik} = 0$ no offer.[13] After observing o_{ik} (and any other relevant state variables), the applicant decides whether or not to enroll in that program, $e_{ik} \equiv e_{ik}(o_{ik}) \in \{0,1\}$, with $e_{ik} = 1$ denoting enrollment and $e_{ik} = 0$ no enrollment. Let $e_{ik}(1) \in \{0,1\}$ denote i's potential enrollment in her kth priority program if offered a slot, and let $e_{ik}(0)$ denote potential enrollment absent an offer. Since in our setting enrollment requires an offer, $e_{ik}(0) = 0$ for all i,k. Hence, the applicant-level objective enrollment return to admission is simply,

$$\Delta^e_{ik} = e_{ik}(1) - e_{ik}(0) \equiv e_{ik}(1). \tag{1}$$

Equation (1) implies that Δ^e_{ik} is observed for applicants who receive an offer for their kth priority program (since then $e_{ik} = e_{ik}(1)$). For applicants without an offer, $e_{ik}(1)$ is counterfactual. Section 5 shows how the cutoff-based variation identifies the relevant average enrollment returns and potential-outcome levels for marginal applicants around the admission cutoff.

Subjective effects Let $\omega_{ik} \in [0,1]$ be applicant i's subjective assessment of $\Pr(o_{ik} = 1)$ after submitting her application but before learning the realized offer,

$$\omega_{ik} = \mathscr{E}_i[o_{ik}],$$

where $\mathscr{E}_i[\cdot]$ denotes i's subjective expectation conditional on her information set at the time of assessment, which coincides with the time of elicitation. Analogously, let $\varepsilon_{ik}(\tilde{o}) \in [0,1]$

[13] To preserve readability, we omit the dependence of k on i. Unless otherwise specified, the subscript ik refers to applicant i's kth ranked program.

be the applicant's subjective assessment of $\Pr[e_{ik}(\tilde{o}) = 1]$ for $\tilde{o} \in \{0, 1\}$,

$$\varepsilon_{ik}(\tilde{o}) = \mathscr{E}_i[e_{ik}(\tilde{o})].$$

The subjective ex ante enrollment return to admission is i's subjective expectation of the objective return Δ^e_{ik}, that is,

$$\mathscr{E}_i[\Delta^e_{ik}] = \mathscr{E}_i[e_{ik}(1) - e_{ik}(0)] = \varepsilon_{ik}(1) - \varepsilon_{ik}(0) \equiv \varepsilon_{ik}(1), \tag{2}$$

where we assume $\varepsilon_{ik}(0) = 0$, reflecting that applicants recognize that enrollment is impossible absent an offer. On the other hand, when evaluating $e_{ik}(1)$, applicants may be uncertain about their enrollment decision if admitted, so we elicit $\varepsilon_{ik}(1)$ on a probabilistic scale from 0 to 100 percent.[14] Importantly, we elicit $\varepsilon_{ik}(1)$ for $k = 1, 2$ from all respondents before admission offers are issued. Hence, unlike their objective counterparts, the subjective ex ante enrollment returns to first-choice and second-choice admissions are observed for everyone at the individual level. Section 5 describes how we compare these subjective objects to their objective counterparts at the same local admissions margin.

3.2 *Belief Accuracy and Decomposition into Sources of Inaccuracy*

Because enrollment requires an offer and completion requires enrollment, applicants' forecasts of unconditional enrollment and completion are naturally expressed in terms of the relevant stage beliefs. To assess belief accuracy, we define forecast errors (FE) as realizations minus forecasts. We begin with those underlying prediction of program enrollment and then move to those underlying prediction of program completion.

Forecast Errors and Belief (In)Accuracy: Enrollment For each applicant, we define three FEs relevant for our analysis of enrollment predictions.

The first FE is the one an applicant makes when using $\mathscr{E}_i\left[\Delta^e_{ik}\right]$ to predict her enrollment response ("return") to being admitted to her kth priority program, Δ^e_{ik}, that is,

$$FE^{\Delta^e}_{ik} = \Delta^e_{ik} - \mathscr{E}_i[\Delta^e_{ik}] \equiv e_{ik}(1) - \varepsilon_{ik}(1), \tag{3}$$

where the right-hand side follows from substituting (1) and (2). In our context, $FE^{\Delta^e}_{ik}$ is therefore the FE in predicting own enrollment in the kth priority program conditional on receiving an admission offer.

[14] Interior subjective probabilities reflect so-called "resolvable" uncertainty (Blass et al., 2010), that is, uncertainty that is due to the incompleteness of the elicitation scenario, but would not be present in an actual choice situation, when the actual choice is made.

The second FE is the one an applicant makes when using ω_{ik} to predict whether she will receive an admission offer for her kth priority program, o_{ik}, that is,

$$FE^{o}_{ik} = o_{ik} - \mathscr{E}_i[o_{ik}] \equiv o_{ik} - \omega_{ik}. \tag{4}$$

Unlike (3), this FE is observed for all applicants because both o_{ik} and ω_{ik} are observed for all applicants.

The third FE is the one an applicant makes when using $\mathscr{E}_i[e_{ik}]$ to predict own enrollment in her kth priority program unconditionally, that is,

$$\begin{aligned} FE^{e}_{ik} &= e_{ik} - \mathscr{E}_i[e_{ik}] \\ &= [o_{ik}e_{ik}(1) + (1-o_{ik})e_{ik}(0)] - \mathscr{E}_i[o_{ik}e_{ik}(1) + (1-o_{ik})e_{ik}(0)] \\ &\equiv o_{ik}e_{ik}(1) - \omega_{ik}\varepsilon_{ik}(1). \end{aligned} \tag{5}$$

The second line makes explicit that realized enrollment depends on whether the applicant receives an offer and, if so, whether she would enroll when offered. Similarly, the forecast $\mathscr{E}_i[e_{ik}]$ is $\mathscr{E}_i[o_{ik}]\mathscr{E}_i[e_{ik}(1)]$ in our setting because $e_{ik}(0) = 0$ and $\varepsilon_{ik}(0) = 0$; that is, $\mathscr{E}_i[e_{ik}] = \omega_{ik}\varepsilon_{ik}(1)$.

To assess the accuracy of each belief, we examine whether the relevant forecast errors in (3)–(5) have mean zero in the relevant (sub)populations.[15] Forecast errors involving offer-conditioned potential outcomes—most directly $FE^{\Delta^e}_{ik}$, which depends on $e_{ik}(1)$—are only observed for applicants who receive offers. Section 5 describes how the cutoff design identifies the corresponding objective counterparts and mean forecast errors at the same local margin.

Decomposing Outcome Beliefs into Sources of Inaccuracy: Enrollment We can express the unconditional enrollment FE (5) as a function of the offer FE (4) and the return FE (3). Simple algebra yields,

$$\begin{aligned} FE^{e}_{ik} &= [o_{ik} - \omega_{ik}]\varepsilon_{ik}(1) + o_{ik}[e_{ik}(1) - \varepsilon_{ik}(1)] \\ &\equiv \underbrace{FE^{o}_{ik}\varepsilon_{ik}(1)}_{\text{system}} + \underbrace{o_{ik}FE^{\Delta^e}_{ik}}_{\text{personal}}. \end{aligned} \tag{6}$$

[15] Alternatively, one could regress the forecasted variable on the forecast and a constant. Under the null of accuracy, the regression slope should be equal to unity and, in absence of aggregate shocks, the regression intercept should be equal to zero. There is a long tradition in economics of empirical tests of rational expectations of this type; see Muth (1961); Lovell (1986); Pesaran and Weale (2006); D'Haultfoeuille et al. (2021); Crossley et al. (2024), among others.

This identity decomposes the forecast error in unconditional enrollment into two components. The first term isolates errors in predicting admission chances (a "system" component), holding fixed the applicant's stated enroll-if-admitted probability. The second term isolates errors in predicting own take-up conditional on an offer (a "personal" component), holding fixed the realized offer.

Decomposing Outcome Beliefs into Sources of Inaccuracy: Completion Let $c_{ik}(\tilde{e}) \in \{0,1\}$ indicate whether applicant i completes her kth priority program conditional on enrollment status $\tilde{e} \in \{0,1\}$, with $c_{ik}(\tilde{e}) = 1$ denoting completion and $c_{ik}(\tilde{e}) = 0$ no completion. 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. We define the objective completion return to enrollment as the causal effect of enrolling on eventual completion,

$$\Delta_{ik}^{c} = c_{ik}(1) - c_{ik}(0) \equiv c_{ik}(1).$$

This captures the effect of enrollment on completion, one step further downstream than Δ_{ik}^{e} in (1). The object Δ_{ik}^{c} is observed for applicants who enroll in the kth priority program (since then $c_{ik} = c_{ik}(1)$); for applicants who do not enroll, $c_{ik}(1)$ is counterfactual. As with enrollment, Section 5 discusses how the cutoff design identifies the corresponding average objects at the relevant local margin.

Let $\chi_{ik}(\tilde{e}) \in [0,1]$ be i's subjective evaluation of $\Pr[c_{ik}(\tilde{e}) = 1]$ for $\tilde{e} \in \{0,1\}$,

$$\chi_{ik}(\tilde{e}) = \mathscr{E}_i\big[c_{ik}(\tilde{e})\big],$$

given i's information set at the time of assessment. Since completion without enrollment is ruled out, the subjective ex ante completion return is,

$$\mathscr{E}_i\big[\Delta_{ik}^{c}\big] = \mathscr{E}_i\big[c_{ik}(1) - c_{ik}(0)\big] = \chi_{ik}(1),$$

in direct analogy to (2). As above, we assume $\chi_{ik}(0) = 0$ and elicit $\chi_{ik}(1)$ probabilistically on a 0–100 scale.

To assess belief accuracy, define the unconditional completion forecast error,

$$\begin{aligned} FE_{ik}^{c} &= c_{ik} - \mathscr{E}_i[c_{ik}] = c_{ik} - \mathscr{E}_i\big[o_{ik}e_{ik}(1)c_{ik}(1)\big] \\ &\equiv c_{ik} - \omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1), \end{aligned} \tag{7}$$

where $\omega_{ik} = \mathscr{E}_i[o_{ik}]$ and $\varepsilon_{ik}(1) = \mathscr{E}_i[e_{ik}(1)]$ were introduced earlier. The term $\omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1)$ is the applicant's forecast of completing the program, expressed as the product of her stated stage beliefs in a setting where completion requires admission and enrollment.[16]

We can decompose FE^c_{ik} 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:

$$\begin{aligned} FE^c_{ik} &= e_{ik}c_{ik}(1) - \omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1) \\ &= [c_{ik}(1) - \chi_{ik}(1)]e_{ik} + \chi_{ik}(1)[e_{ik} - \omega_{ik}\varepsilon_{ik}(1)] \\ &\equiv \underbrace{FE^{\Delta^c}_{ik}e_{ik}}_{\text{persistence}} + \underbrace{\chi_{ik}(1)FE^e_{ik}}_{\text{intention}}, \end{aligned} \tag{8}$$

where

$$FE^{\Delta^c}_{ik} = c_{ik}(1) - \chi_{ik}(1), \quad FE^e_{ik} = e_{ik} - \omega_{ik}\varepsilon_{ik}(1).$$

In this decomposition, $FE^{\Delta^c}_{ik}e_{ik}$ isolates errors in predicting persistence conditional on enrollment, whereas $\chi_{ik}(1)FE^e_{ik}$ scales the enrollment forecast error by the applicant's belief about completion. Combined with (6), this structure allows the empirical analysis to pinpoint whether inaccuracy in overall completion predictions stems primarily from errors in beliefs about admission chances, from errors in predicted take-up conditional on admission, or from errors in predicted persistence once enrolled.

4 Data Sources and Description

Our empirical analysis relies on linking individual-level survey responses to administrative records. Subsection 4.1 describes our expectations survey among Norwegian college applicants. Subsection 4.2 describes the various registers of Norwegian administrative records we draw data from. Subsection 4.3 describes the analytic sample of the linked survey-administrative data set that we use in the empirical analysis.

4.1 Survey

The survey we fielded targeted over 20,000 individuals born between 1997 and 1999, who applied to higher education in Norway in the spring of 2018 through NUCAS. 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 offers were released.

The main purpose of the survey was to elicit applicants' preferences over programs; their subjective expectations over admission, enrollment conditional on admission, and

[16] As with enrollment, one can test whether FE^c_{ik} has mean zero by regressing c_{ik} on $\omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1)$ (with unit slope under the null of accuracy), or by examining the sample mean of FE^c_{ik} directly.

subsequent outcomes; and other information relevant for understanding applicants' beliefs and behavior. About 9,000 applicants to over 800 different study programs responded to our survey.[17]

The survey elicited a broad range of subjective expectations over outcomes associated with the 1st and 2nd priority programs each respondent indicated in her application. These include the probabilities of admission, enrollment given admission, and completion given enrollment, which are the main focus of our analysis. They further include multiple GPA-related expectations conditional on program enrollment (i.e., expected GPA, probability of above-average GPA, probability of below-average GPA, and expected GPA rank), and multiple earning-related expectations in the applicant's first job and at age 45 conditional on program completion (i.e., expected earnings, probability of expected earnings plus 15%, and probability of expected earnings minus 15%). We use this additional set of beliefs in the counterfactual analysis of Section 8.

With the exception of expected GPA (scale 1-6) and expected earnings (today wage levels before taxes), each belief was elicited using a numerical scale of percent chance ranging from 0 percent to 100 percent.[18] In the analysis below, we focus on the following objects, with $k \in \{1,2\}$:

$$\begin{aligned}
&\Pr(i \text{ is admitted to } k\text{th priority} = 1);\\
&\Pr(i \text{ enrolls in } k\text{th priority} = 1 \mid i \text{ is admitted to } k\text{th priority} = 1);\\
&\Pr(i \text{ enrolls in } k\text{th priority} = 1);\\
&\Pr(i \text{ graduates from } k\text{th priority} = 1 \mid i \text{ enrolls in } k\text{th priority} = 1);\\
&\Pr(i \text{ graduates from } k\text{th priority} = 1).
\end{aligned}$$

Furthermore, the survey elicited additional information potentially relevant for understanding individuals' beliefs and behavior, including the respondent's attitudes toward time, risk, and competition.

[17] Specifically, we targeted 20,240 individuals, corresponding to approximately one-third of the relevant population. The latter comprises all applicants to higher education in Norway in the spring/summer 2018 through NUCAS. We targeted a stratified sample from the population, as following: (A) 50% of students in their final high school year (1999 cohort) who indicated on their submitted application a (predicted to be) oversubscribed 1st-choice program; (B) 45% of high school graduates (1997-1998 cohorts) who indicated on their submitted application a (predicted to be) oversubscribed 1st-choice program (these include students who took a break after high school and second-time applicants); and (C) 5% of students whose 1st-choice program on the submitted application was not (predicted to be) oversubscribed. Participation rates were 42% among (A), 47% among (B), 40% among (C), and 44% overall.

[18] We elicit the probability of admission to the 2nd-choice program conditional on no admission to the 1st-choice program, and combine it with the 1st-choice admission belief to construct the unconditional 2nd-choice admission belief.

4.2 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. 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. Finally, we know our treatment and outcome variables from the national education register (through 2024).[19]

4.3 Sample

Table 1 reports descriptive statistics (means and, for non-binary variables, standard deviations) of relevant background characteristics in our analytic sample, comprising the subset of respondents to our survey whose 1st-choice program in the application was oversubscribed and who were on the margin between their 1st- and 2nd-ranked programs.[20] In practice, this is the subset for whom crossing the first-choice cutoff changes the offer from the second-choice program to the 1st-choice program.

68% of sample applicants are female. 45% are 19 years old, 33% are 20 years old, and 22% are 21 years old. 63% are first-time applicants. 69% have at least one college-educated parent. The average application score is 50.6 and the standard deviation is 6.9.[21] Risk tolerance and competitiveness score and the time patience score are normalized to be mean zero and have standard deviations of 0.61 and 0.39, respectively.[22] People apply to a wide range of programs, which we group into five broad categories, whose prevalence varies from 11 percent in Teaching and 31 percent in Health.

Table 2 presents applicants' subjective beliefs about the likelihoods of admission, enrollment given admission, and completion given enrollment, and contrasts them with realized admission, enrollment, and completion among the same students, for students' 1st-choice program (Col. 1-4) and 2nd-choice program (Col. 5-8). Specifically, Columns (1) and (5) show the relevant sample means, and, only for the subjective beliefs, the remaining columns reports the standard deviations (Col. 2 and 6), the percentage of "0

[19]NUCAS classifies specific fields into broad fields. This classification is different from the one used by the national education registry, http://www.ssb.no/a/publikasjoner/pdf/nos_c617/nos_ c617.pdf. We recoded the information on individuals' educational attainment to match that of the admission service.

[20]This implies that their 2nd-ranked program was either not oversubscribed, or oversubscribed but the applicants application score exceeded the 2nd-ranked program's application threshold.

[21]Recall that high-school grades in individual subjects range from 1 to 6 (integers only). The GPA is obtained by taking the average across subjects (rounded to the second decimal place) and multiplying it by 10. Hence, an individual's GPA ranges from 10 to 60.

[22]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

	Mean	**Standard Deviation**
	(1)	(2)
Female	0.68	-
Age 19	0.45	-
Age 20	0.33	-
Age 21	0.22	-
First-time applicant	0.63	-
Has college-educated parent/s (at least one)	0.69	-
Ability (application score)	50.6	6.9
Risk tolerance & competitiveness score (normalized)*	0	0.55
Time patience score (normalized)*	0	0.39
Field of study		
- Social Science & Humanities	0.18	-
- Science & Engineering	0.23	-
- Law & Business	0.17	-
- Teaching	0.11	-
- Health	0.31	-
N	4,206	

Note: * N for risk and time scores is 3,600.

percent" responses (Col. 3 and 7), and the percentage of "100 percent" responses (Col. 4 and 8).

On average, applicants overestimate the likelihood of all three outcomes for their 1st-choice program and of two out of three outcomes for their 2nd-choice program. Indeed, applicants overestimate their likelihood of being admitted to their 1st choice by 9 percentage points (mean subj prob = 72 percent vs. % admitted = 63), that of enrolling in their 1st choice if admitted by 7 percentage points (among the admitted, mean subj prob = 85 percent vs. % enrolled = 78); and that of completing their 1st choice if enrolled by 22 percentage points (among the enrolled, mean subj prob = 89 percent vs. % completed = 67).[23,24]

The mean gap between realized and expected enrollment in the 2nd choice if admitted is equal to that for the 1st choice, despite the lower levels (mean subj prob = 65 percent vs. % enrolled = 58); whereas the gap between realized and expected completion in the 2nd choice if enrolled is over twice as large as that for the 1st choice (mean subj prob

[23] In the overall sample, the mean subjective probability of enrolling in one's 1st-choice program if admitted is 81 percent and the mean subjective probability of completing one's 1st-choice program if enrolled is 89 percent.

[24] The elicited probabilities refer to any-time completion and we observe education outcomes up to and including 2024. Appendix Figure A1 compares on-time completion across cohorts and completion by time since first enrollment. We see that our main study cohort (2018) is very comparable to surrounding cohorts, and that by 2024 (6 years since enrollment) we capture near all completion.

= 87 percent vs. % completed = 41). On the other hand, applicants underestimate the likelihood of being admitted to their 2nd choice if not admitted to their 1st choice (mean subj prob = 27 percent vs. % admitted = 36).

The statistics shown in the remaining columns of Table 2 reveal the existence of substantial heterogeneity in applicants' subjective expectations and in how (un)certain applicants feel about their admission, enrollment, and completion prospects. In particular, 42% of sample applicants expect to be admitted to their 1st-choice program with certainty, 6% expect not to be admitted with certainty, whereas the remaining 52% of applicants express uncertainty about their admission prospects by reporting a subjective probability strictly interior to the 0-100 percent-chance range. The corresponding figures for the 2nd-choice program are 3%, 30%, and 77%, suggesting more widespread uncertainty.

Conditional on (hypothetically) being admitted in their 1st-choice program, a large majority of applicants expect to enroll with certainty (69% among those actually admitted and 64% in the overall sample), about a quarter report being uncertain about whether they will enroll (25% among the admitted and 29% in the overall sample), and the remaining 6-7% expect not to enroll for sure. The corresponding figures for the 2nd-choice program are 35% and 38% (certain to enroll), 53% and 46% (uncertain), 12% and 16% (certain not to enroll), again suggesting more widespread uncertainty.

Concerning the likelihood of completing one's 1st choice conditional on enrolling, no applicant assigns a 0 percent chance to this event, while about 40% of applicants who actually enrolled in their 1st choice assign a 100 percent chance to the event, the remaining 60% expressing uncertainty about completion. In this case, the corresponding figures for the 2nd-choice program are broadly similar to those for the 1st-choice program.[25]

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 take advantage of the resulting fuzzy RDD (FRDD) to identify and estimate the enrollment returns to being admitted to one's 1st-choice program in relevant subpopulations of applicants and to compare

[25]The full extent of belief heterogeneity in our sample of applicants is shown in Appendix Figure A2, which plots the sample distributions of applicants' subjective probabilities of admission, enrollment given admission, and completion given enrollment, for their 1st-choice program. As customary for survey-measured numerical probabilities elicited on a 0-100 percent-chance scale, the histograms reveal some bunching at multiples of 10 percent and, to a lesser extent, at multiples of 5 percent, suggesting that responses may be rounded to the nearest 5 or 10 percent (e.g., see Giustinelli et al. (2022) for recent evidence and discussion). However, the extent of bunching does not seem severe, perhaps with the exception of 100 percent responses, presumably indicating complete (or almost complete) confidence in the occurrence of the corresponding event.

Table 2. Applicants' Outcomes: Expectations (Subj prob) and Realizations (Actual)

	1st-choice program (k=1)				**2nd-choice program** (k=2)			
	Mean (1)	Std. Dev. (2)	% 0 (3)	% 100 (4)	Mean (5)	Std. Dev. (6)	% 0 (7)	% 100 (8)
Admission (Offer)								
- Subj prob (all)	0.72	0.36	6	42	0.27	0.34	30	3
- Actual (all)	0.63	-	-	-	0.36	-	-	-
Enrollment | Admission								
- Subj prob (admitted)	0.85	0.30	6	69	0.65	0.39	12	35
- Subj prob (all)	0.81	0.34	7	64	0.59	0.41	16	28
- Actual (admitted)	0.78	-	-	-	0.58	-	-	-
Completion | Enrollment								
- Subj prob (enrolled)	0.89	0.16	0	40	0.87	0.21	0	40
- Subj prob (all)	0.89	0.17	0	41	0.83	0.23	1	31
- Actual (enrolled)	0.67	-	-	-	0.41	-	-	-
N	4,206				3,284			

Note: In the row labels, round brackets report the conditioning sample: "all" indicates all applicants, "admitted" conditions on the admitted applicants, and "enrolled" conditions on the enrolled ones.

these estimates with estimates of subjective returns obtained from subjective expectations data we collected in our design-coordinated survey of college applicants.

This section spells out what the admission cutoffs identify and how we estimate the objects used in the analysis. We use linear two-stage least squares (2SLS) throughout, using predicted admission based on the first-choice cutoff as an instrument. 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; and (iii) observed "all treated" levels just above the cutoff, which align with belief questions that condition on receiving an offer.

5.1 Identification of Potential Outcomes that Map to the Elicited Beliefs

The belief questions elicit probabilities of enrolling and completing conditional on being offered the 1st- or 2nd-ranked program. The cutoff-based variation therefore identifies the corresponding potential-outcome levels locally, including principal-strata objects in which the relevant counterfactual to a 1st-choice offer is a 2nd-choice offer. We begin by defining offer states and principal strata at the 1st-choice cutoff and then show how simple 2SLS/Wald ratios recover the complier and principal-stratum levels.[26]

We now use the one-offer feature of the mechanism to define principal strata at the 1st-choice cutoff and show which potential-outcome levels are identified. To simplify notation, in this subsection we omit the i subscript. Let $Z_1 \in \{0,1\}$ indicate whether the applicant is or not (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 offer state the applicant would obtain under $Z_1 = z_1$, where $D = 1$ corresponds to an offer of the 1st-ranked program, $D = 2$ to an offer of the 2nd-ranked program, and $D = 0$ to no offer of either the 1st- or 2nd-ranked program. For any outcome Y (enrollment, completion, or completion conditional on enrolling), let $Y(d)$ denote the potential outcome under offer state $D = d$, which is the object directly matched to the elicited beliefs "if offered 1st/2nd choice."

Principal strata are defined by the pair $\{D(0), D(1)\}$. Table 3 lists all logical types; entries "struck through" are ruled out by the single-offer constraint and monotonicity at the first-choice 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 enroll in their 1st-choice program if admitted ($Z_1 = 1$), but would respond differently to no 1st-choice admission: $C2$ types would enroll in their 2nd-ranked program, whereas $C0$ types would do something else (e.g., pass and take the year off).

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 $j \in \{0,1,2\}$, then these shares are identified directly from first stages, as follows:

$$\Delta D_1 \equiv E[D_1 \mid Z_1 = 1] - E[D_1 \mid Z_1 = 0] = p^{C0} + p^{C2}, \quad -\Delta D_2 = p^{C2}, \quad -\Delta D_0 = p^{C0},$$

where $D_0 \equiv \mathbf{1}\{D = 0\}$ and Δ denotes the (locally controlled) difference across the cutoff.

Write

$$p \equiv \frac{p^{C0}}{p^{C0} + p^{C2}} = \frac{-\Delta D_0}{\Delta D_1},$$

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

[26]Principal stratification is a "*cross-classification of subjects defined by the joint potential values of* [the] *post-treatment variable under each of the treatments being compared*." (Frangakis and Rubin, 2002). Principal stratification analysis generalizes the textbook local average treatment effect instrumental variables (LATE-IV) case with binary assignment and binary treatment (Imbens and Rubin, 2015). We formally

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

	$D(0)$	$D(1)$
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

	$Z_1 = 0$	$Z_1 = 1$
D=1	A1, ~~DF2, DF0~~	A1, C2, C0
D=2	A2, C2, ~~X0~~	A2, ~~DF2, X2~~
D=0	A0, C0, ~~X2~~	A0, ~~DF0, X0~~

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,

$$\begin{aligned} E[Y \cdot D_1 \mid Z_1 = 1] &= E[Y(1) \mid C0]\, p^{C0} + E[Y(1) \mid C2]\, p^{C2} \\ &\quad + E[Y(1) \mid A1]\, \Pr(A1), \\ E[Y \cdot D_1 \mid Z_1 = 0] &= E[Y(1) \mid A1]\, \Pr(A1), \\ \frac{E[Y \cdot D_1 \mid Z_1 = 1] - E[Y \cdot D_1 \mid Z_1 = 0]}{E[D_1 \mid Z_1 = 1] - E[D_1 \mid Z_1 = 0]} &= E[Y(1) \mid C0]\; p + E[Y(1) \mid C2]\; (1-p), \end{aligned} \tag{9}$$

identifies the complier mean under 1st-choice access as a mixture of the two complier strata.

Because D_2 falls at the 1st-choice cutoff for $C2$, we work with 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 $E[Y(0) \mid C0]$.

The standard 2SLS coefficient from (11)-(12) can be written as,

$$\tau = p\big(E[Y(1) \mid C0] - E[Y(0) \mid C0]\big) + (1-p)\big(E[Y(1) \mid C2] - E[Y(2) \mid C2]\big),$$

define the relevant principal strata in our setting below.

linking the overall "return of access" to the two principal-strata contrasts. Equation (9) identifies the corresponding mixture of 1st-choice potential-outcome levels, while the sign-flipped Wald ratios for D_2 and D_0 identify $E[Y(2) \mid C2]$ and $E[Y(0) \mid C0]$. Together with τ and the identified weight p, these moments deliver the potential-outcome levels we report in the principal-strata tables and figures.

Equation (9) identifies the complier mean under 1st-choice access as a mixture of the two complier strata, $C0$ and $C2$. Without further restrictions, $E[Y(1) \mid C2]$ is therefore not point-identified from the 1st-choice cutoff alone, because the observed complier mean under $D = 1$ aggregates applicants who would otherwise receive no offer ($C0$) and applicants who would otherwise receive the 2nd choice ($C2$).

Our target objects are the $C2$ counterfactuals, for which the relevant alternative to 1st-choice access is 2nd-choice access. Empirically, we therefore restrict attention to applicants who are above the 2nd-choice cutoff in the local window, so that the mass of $C0$ types is small. In this restricted sample, the first-stage estimates imply that p^{C0} is approximately 0.03, so that the mixture weight $p = p^{C0}/(p^{C0} + p^{C2})$ is close to zero and the identified complier mean under $D = 1$ is numerically close to $E[Y(1) \mid C2]$.

We also report no-assumption bounds for the $C2$ levels (and the corresponding 1st-minus-2nd contrasts) obtained by combining the identified mixture with the logical restriction $Y(1) \in [0,1]$. Specifically, if $m \equiv pE[Y(1) \mid C0] + (1-p)E[Y(1) \mid C2]$ denotes the identified mixture in (9), then

$$E[Y(1) \mid C2] \in \left[\max\left\{0, \frac{m-p}{1-p}\right\}, \min\left\{1, \frac{m}{1-p}\right\}\right], \tag{10}$$

and the square brackets in the principal-strata tables report these bounds.

5.2 *Estimation*

We estimate the objects of interest using linear 2SLS regressions, with local controls $g_k(h)$ defined below. Depending on the estimand, the endogenous regressor is either the 1st-choice offer indicator D_{1ik} (offer-based estimands) or enrollment (enrollment-based estimands). Similarly, the outcome Y is enrollment, completion (unconditional or conditional on starting), or the matching elicited belief. This approach ensures that the objective objects and their belief counterparts are computed at the same local margin.

Applicants i submit a ranked list of programs. For each applicant we study the cutoff relevant for her 1st-ranked program; to simplify notation, we index the resulting observation by i,k and suppress the dependence of k on i. Let $h_{ik} = \text{score}_{ik} - \text{cutoff}_k$ denote distance to the 1st-choice cutoff for program k and $Z_{ik} = \mathbf{1}\{h_{ik} \geq 0\}$ the threshold indicator.[27] Let $D_{1ik} \in \{0,1\}$ indicate an offer of the 1st-ranked program and $D_{2ik} \in \{0,1\}$ an offer of the 2nd-ranked program. The centralized mechanism yields at most one offer locally, so $D_{1ik}D_{2ik} = 0$. Outcomes $Y_{ik} \in \{0,1\}$ include enrollment and completion; completion conditional on enrolling is reported as the ratio of completion-per-offer to enrollment-per-offer objects.

For a given outcome Y, within a symmetric window around $h_{ik} = 0$, we estimate,

$$Y_{ik} = \alpha_k + \tau D_{1ik} + g_k(h_{ik}) + u_{ik}, \tag{11}$$

$$D_{1ik} = \gamma_k + \pi Z_{ik} + g_k(h_{ik}) + v_{ik}, \tag{12}$$

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

In addition to effects, the belief comparisons require potential-outcome levels. These are linear 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 in Section 5.1 by running the same local specifications with dependent variables $Y_{ik}D_{jik}$ and D_{jik} for $j \in \{0,1,2\}$, where $D_{0ik} \equiv \mathbf{1}\{D_{1ik} = 0,\ D_{2ik} = 0\}$. For descriptive comparisons for the admitted ("all treated") group, we report conditional means $E[Y_{ik} \mid D_{jik} = 1]$ and the corresponding beliefs evaluated in the same program/score window (for $j = 1$ or $j = 2$), without a causal interpretation.

We conduct standard RD diagnostics. These include a density test for manipulation around the admission cutoff in Appendix Figure A3; balancing tests for predetermined characteristics and subjective expectations at the cutoff in Appendix Table A2 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 Tables A4-A7 we re-estimate potential outcomes and effects using bias-corrected local-linear regression with MSE-optimal bandwidths, based on Kolesár and Rothe (2018)'s nonparametric `rdhonest`. These estimates are close to the baseline 2SLS results.

6 Elicited Beliefs and Counterfactual Outcomes

In this section, we present the principal-strata estimates for $C2$ applicants, whose relevant alternative to not receiving a 1st-choice admission (offer) is receiving a 2nd-choice admis-

[27] This Z_{ik} corresponds to Z_1 in Subsection 5.1, with indexing restored.

sion (offer). The estimates are shown in Table 4. For each outcome Y—enrollment and completion, with completion shown both per offer and conditional on enrollment—the left panel of the table reports objective complier potential-outcome levels under 1st- and 2nd-choice access, y^1 and y^2, and the corresponding contrast, $y^1 - y^2$. The right panel of the table reports the belief-implied counterparts, constructed from elicited probabilities using the same conditioning ("if offered 1st/2nd choice") and the same local sample window. All entries are estimated using the linear 2SLS procedures described in Section 5. Appendix Tables A4-A6 report the corresponding estimates of objective and subjective y^1 and y^2 for $C2$ applicants as well as for additional groups ($C2C0$, $C0$, $A1$, and $A2$), in unbalanced and balanced samples. Appendix Figure A7 presents the same estimates graphically.

In this table and discussion, labels of the form Outcome(State) (i.e., Enroll(Offer), Complete(Offer), and Complete(Enroll)) denote the corresponding causal estimands. For enrollment per offer, switching the offer from the 2nd choice to the 1st choice raises enrollment from 0.61 to 0.74, an objective effect or "return" of 0.12. Marginal ($C2$) applicants expect a somewhat larger change, from 0.60 to 0.85, corresponding to subjective effect or " return" of 0.24. This overestimation of the enrollment response to 1st- versus 2nd-choice access by applicants at the margin between their 1st- and 2nd-choice programs is not driven by their underestimating own enrollment response to a 2nd-choice offer, as applicants' expected 2nd-choice take-up is close to the actual one (0.60 versus 0.61). Instead, the discrepancy comes from overestimating own enrollment response to a 1st-choice offer, with an expected 1st-choice take-up substantially higher than the actual one (0.85 versus 0.74).

For completion per offer, switching the offer from the 2nd choice to the 1st choice raises completion from 0.28 to 0.41, an objective effect or return of 0.13. Once again, applicants expect a larger change, from 0.52 to 0.77, corresponding to a subjective effect or return of 0.25. The overestimation comes from applicants substantially overestimating their completion likelihood under both access states: 0.77 versus 0.41 under 1st-choice access and 0.52 versus 0.28 under 2nd-choice access.

Conditional on enrollment, completion is 0.45 under 2nd-choice access and 0.53 under 1st-choice access, with a wide standard error on the contrast. As before, applicants widely overestimate their completion likelihood under both states: 0.84 versus 0.45 under 2nd-choice access and 0.91 versus 0.53 under 1st-choice access. However, this time the persistence contrast is small in both realization and belief spaces, so the perceived effect happens to be approximately accurate.

The two-sided 1st-versus-2nd comparisons presented in this section isolate the perceived incremental value of the first choice relative to the closest feasible substitute at

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

	Objective **Outcomes and Effects**			*Subjective* **Outcomes and Effects**		
	y^1 (1)	y^2 (2)	$y^1 - y^2$ (3)	$\mathscr{E}[y^1]$ (4)	$\mathscr{E}[y^2]$ (5)	$\mathscr{E}[y^1 - y^2]$ (6)
Enroll(Offer)	0.74	0.61	0.12	0.85	0.60	0.24
	(0.046)	(0.060)	(0.075)	(0.030)	(0.047)	(0.057)
	[0.73-0.76]		[0.11-0.15]			
Complete(Offer)	0.41	0.28	0.13	0.77	0.52	0.25
	(0.053)	(0.050)	(0.073)	(0.032)	(0.045)	(0.059)
	[0.39-0.43]		[0.11-0.14]			
Complete(Enroll)	0.53	0.45	0.08	0.91	0.84	0.06
	(0.071)	(0.071)	(0.110)	(0.020)	(0.026)	(0.032)
	[0.41-0.65]		[-0.04-0.20]			

Notes: In the row labels, Y(D) denotes the corresponding IV estimand (i.e., outcome Y under treatment state D). Standard errors are reported in round brackets under the respective point estimates. Estimated no-assumption bounds for y^1 and $y^1 - y^2$ based on Eq. (10) are reported in square brackets.

the cutoff margin, while also revealing substantial level forecast errors in downstream outcomes. In the next section, we try to shed light on the underlying mechanisms by investigating where the belief-outcome discrepancies documented in this section enter the outcome sequence.

7 Mechanisms: Decomposing Belief Inaccuracies

In this section, we use the forecast-error decompositions derived in Section 3 to locate the sources of the discrepancies documented in the previous section, separating (i) mistakes about the admission probabilities (system component) from mistakes about own take-up conditional on being admitted (personal component), and (ii) mistakes about unconditional enrollment (intention component) from mistakes about completion once enrolled (persistence component). Throughout, forecast errors (FE) are defined as actual minus expected.

7.1 Decomposing Belief Inaccuracy: Enrollment

We now implement empirically the decomposition of the unconditional enrollment FE into the admission FE and the enrollment-given-admission FE, formalized in Eq. (6). Recall that the first term, which we labelled "system component," isolates misprediction of the admission probability for a given program holding fixed the applicant's expectation of enrolling in that program if admitted; whereas the second term, which we labelled "personal component," isolates misprediction of the take-up response ("return") to being admitted to that program holding fixed the realized offer state.[28] We report results in Table 5, separately for applicants' 1st-choice program (top panel) and 2nd-choice program (bottom panel) and for marginal applicants (left panel, Col. 1-2) and all treated applicants (right panel, Col. 3). For each of the two programs and groups of applicants, the table provides estimates (along with standard errors in parentheses) of the following terms: (a) system component, (b) personal component, and (c) total FE. Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS) in Col. (1), and bias-corrected local-linear regression with MSE-optimal bandwidths, based on Kolesár and Rothe (2018)'s nonparametric `rdhonest`, in Col. (2). Robust standard errors are shown in parentheses next to the point estimates. The table further provides a mean squared errors (MSE) decomposition, including a cross term, $2\mathbb{E}[(a)\cdot(b)]$. Appendix Figure A9 plots the same objects, (a)-(c), by distance to the admission threshold.

For the 1st-choice program, marginal applicants underpredict admission: the system component is $+0.08$ to $+0.09$ and statistically different from zero. The personal component is -0.05, implying modest overprediction of take-up conditional on admission (consistent with the negative return forecast errors in Appendix Table A7). The two components therefore offset each other, leaving a small positive total unconditional enrollment FE of about $+0.04$.[29] Among all treated applicants, the system component remains positive ($+0.06$), while the personal component is more negative (-0.08), yielding a small negative total FE of about -0.01.

For the 2nd-choice program, the magnitudes are larger. Among marginal applicants, the system component is $+0.32$ to $+0.33$, and the personal component is $+0.08$ to $+0.09$, implying a large positive total unconditional enrollment FE of about $+0.42$. Under the actual-minus-expected convention, this indicates substantial underprediction of unconditional enrollment into the 2nd-ranked program driven both by underprediction of the likelihood of receiving a 2nd-choice offer and by underprediction of take-up conditional on receiving it (consistent with the positive return forecast errors in Appendix Table A7). Among all treated applicants, the system component remains sizeable ($+0.25$), but the personal component is negative (-0.05), so overprediction of take-up conditional on a

[28]The personal component is proportional to the enrollment return forecast error, $FE_{ik}^{\Delta^e}$. Appendix Table A7 reports estimates of the mean return FE and of its underlying components, separately for 1st-choice program (top panel) and 2nd-choice program (bottom panel), and for marginal applicants (left panel, Col. 1-2) and all treated applicants (right panel, Col. 3). For marginal applicants, the table shows both parametric 2SLS estimates (Col. 1) and non-parametric RD estimates (Col. 2). Appendix Figure A8 plots the same objects by distance to the admission threshold.

[29]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): System (Admit) vs Personal (Enroll | Admit) Components

	Marginal Applicants				All Treated	
	(1)	MSE	(2)	MSE	(3)	MSE
1st-choice program (k=1)						
(a) System: Admit	0.09 (0.02)	0.02	0.08 (0.03)	0.02	0.06 (0.00)	0.09
(b) Personal: Enroll | Admit	-0.05 (0.03)	0.07	-0.05 (0.03)	0.06	-0.08 (0.01)	0.02
Cross term		0.00		-0.00		-0.01
(c) Total FE: Enroll (uncond.)	0.04 (0.04)	0.10	0.04 (0.03)	0.08	-0.01 (0.01)	0.10
N	2,869		2,869		2,594	
2nd-choice program (k=2)						
(a) System: Admit	0.33 (0.03)	0.18	0.32 (0.04)	0.18	0.25 (0.01)	0.14
(b) Personal: Enroll | Admit	0.09 (0.06)	0.20	0.08 (0.05)	0.19	-0.05 (0.01)	0.21
Cross term		0.01		0.01		-0.09
(c) Total FE: Enroll (uncond.)	0.42 (0.06)	0.39	0.42 (0.06)	0.38	0.20 (0.01)	0.26
N	2,234		2,234		1,250	
Estimator	2SLS		Non-par.			

Notes: (a) System: Admit ($FE^{o}_{ik}\varepsilon_{ik}(1)$) + (b) Personal: Enroll | Admit ($o_{ik}FE^{\Delta^e}_{ik}$) = (c) Total FE: Enroll (uncond., FE^{e}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS) in Col. (1) and bias-corrected local-linear regression with MSE-optimal bandwidths, based on Kolesár and Rothe (2018)'s nonparametric rdhonest, in Col. (2). Robust standard errors are shown in parentheses next to the point estimates. The mean squared errors (MSE) decomposition is reported in the adjacent column. This includes a cross term, corresponding to the interaction term of the MSE decomposition (i.e., $2\mathbb{E}[(a)\cdot(b)]$).

second-choice offer partially offsets underprediction of the offer state; the resulting total FE remains positive at $+0.20$.

Unconditional enrollment FE is driven primarily by errors in forecasting admission, with especially large system components for 2nd-choice offers. Errors in take-up conditional on admission are smaller but materially affect the aggregate FE through offsetting: for 1st-choice enrollment they largely offset admission misprediction, while for 2nd-choice enrollment they reinforce admission misprediction among marginal applicants and partially offset it among all treated. Appendix Figure A9 is consistent with this interpretation, with the system component varying more with distance to the cutoff than the personal component.

7.2 *Decomposing Belief Inaccuracy: Completion*

Next, we implement empirically the decomposition of the unconditional completion FE into the enrollment FE and the completion-given-enrollment FE, formalized in equation (8). Recall that the first term, which we labelled "persistence component," isolates mis-

Table 6. Decomposition of Unconditional Completion Forecast Error (FE): Intention (Enroll) vs Persistence (Complete | Enroll) Components

	Marginal Applicants				All Treated	
	(1)	MSE	(2)	MSE	(3)	MSE
1st-choice program (k=1)						
(a) Intention: Enroll	0.03 (0.03)	0.07	0.04 (0.03)	0.05	-0.01 (0.01)	0.08
(b) Persistence: Complete	Enroll	-0.28 (0.05)	0.32	-0.28 (0.04)	0.33	-0.24 (0.01)	0.27
Cross term		-0.07		-0.07		-0.05
(c) Total FE: Complete (uncond.)	-0.25 (0.05)	0.32	-0.24 (0.05)	0.32	-0.25 (0.01)	0.30
N	2,869		2,869		2,594	
2nd-choice program (k=2)						
(a) Intention: Enroll	0.35 (0.05)	0.28	0.34 (0.05)	0.27	0.17 (0.01)	0.20
(b) Persistence: Complete	Enroll	-0.30 (0.05)	0.32	-0.28 (0.05)	0.30	-0.27 (0.01)	0.28
Cross term		-0.35		-0.34		-0.25
(c) Total FE: Complete (uncond.)	0.04 (0.05)	0.26	0.06 (0.05)	0.22	-0.10 (0.01)	0.24
N	2,234		2,234		1,250	
Estimator	2SLS		Non-par.			

Notes: (a) Intention: Enroll ($\chi_{ik}(1)FE^{e}_{ik}$) + (b) Persistence: Complete | Enroll ($FE^{\Delta^c}_{ik}e_{ik}$) = (c) Total FE: Complete (uncond., FE^{c}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS) in Col. (1) and bias-corrected local-linear regression with MSE-optimal bandwidths, based on Kolesár and Rothe (2018)'s nonparametric rdhonest, in Col. (2). Robust standard errors are shown in parentheses next to the point estimates. The mean squared errors (MSE) decomposition is reported in the adjacent column. This includes a cross term, corresponding to the interaction term of the MSE decomposition (i.e., $2\mathbb{E}[(a)\cdot(b)]$).

prediction of the completion return to enrolling in that program holding fixed realized enrollment; whereas the second term, which we labelled "intention component," isolates misprediction of the unconditional enrollment probability for a given program holding fixed the applicant's expectation of completing that program after enrolling.

We report results in Table 6, as before, separately for applicants' 1st-choice program (top panel) and 2nd-choice program (bottom panel) and for marginal applicants (left panel, Col. 1-2) and all treated applicants (right panel, Col. 3). For each of the two programs and groups of applicants, the table provides estimates (along with standard errors in parentheses) of the following terms: (a) intention component, (b) persistence component, and (c) total FE. Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS) in Col. (1) and bias-corrected local-linear regression with MSE-optimal bandwidths, based on Kolesár and Rothe (2018)'s nonparametric `rdhonest`, in Col. (2). Robust standard errors are shown in parentheses next to the point estimates. The table further provides a mean squared errors (MSE) decomposition, including a cross term, $2\mathbb{E}[(a)\cdot(b)]$. Appendix Figure A10 plots the same objects, (a)-(c), by distance to the admission threshold.

For the 1st-choice program, the intention component is small: $+0.03$ to $+0.04$ for marginal applicants and -0.01 for all treated applicants, mirroring the sign differences in the unconditional enrollment FEs in Table 5. The persistence component is large and negative in both samples, about -0.28 for marginal applicants and -0.24 for all treated applicants. Under the actual-minus-expected convention, this implies substantial overestimation of completion conditional on enrollment. As a result, the total unconditional completion FE is large and negative, about -0.24 to -0.25 for marginal applicants and -0.25 for all treated applicants. For first-choice completion, FEs are therefore driven overwhelmingly by persistence rather than by enrollment intentions.

For the second-choice program, the intention component is large and positive in both samples, $+0.34$ to $+0.35$ for marginal applicants and $+0.17$ for all treated applicants, consistent with the sizeable positive unconditional enrollment FEs for second-choice offers in Table 5. The persistence component remains negative and sizeable, about -0.28 to -0.30 for marginal applicants and -0.27 for all treated applicants. Among marginal applicants, the two components largely offset each other, leaving a small positive total unconditional completion FE of $+0.04$ to $+0.06$. Among all treated applicants, persistence dominates the intention component, yielding a negative total FE of about -0.10.

We find that completion FE is primarily a persistence phenomenon: applicants substantially overstate completion conditional on enrollment under both 1st- and second-choice programs and in both groups (marginal and all treated). Differences in unconditional completion FEs across program ranks and applicant groups reflect how this persistence optimism combines with enrollment-intention errors, which are small for first-choice admission but large for second-choice offers. Appendix Figure A10 reports the same decomposition by distance to the cutoff.

7.3 Heterogeneity in Forecast Errors

We further examine whether the decomposition components vary systematically across applicants. We summarize the qualitative patterns here and report the full set of subgroup decompositions in Appendix Tables A8-A19.

Across splits and for both the 1st-choice and 2nd-choice objects, heterogeneity in unconditional enrollment FEs reflects variation in both underlying components (system and personal). Differences in beliefs about admission (system component) are pronounced for splits that proxy system familiarity (e.g., parental education) or prior achievement (e.g., GPA), consistent with more accurate perceptions of the admissions process among applicants with more information or stronger prior performance. In other splits (notably gender and application experience), gaps in beliefs about enrollment conditional on admission (personal component) are often comparable in magnitude to gaps in the system component, and the two components can partially offset. As a result, differences in unconditional enrollment FEs across groups are not mechanically determined by any single component.

For completion, FEs are dominated by completion-given-enrollment (persistence component). Overoptimism about persistence is pervasive across groups, and differences by prior achievement are substantial: higher-GPA applicants are less overoptimistic about completing conditional on enrolling. Both novice and experienced applicants substantially overestimate persistence, and we do not find a consistent novice–experienced gradient in this error at the admission margin. Overall, variation in persistence beliefs is more consequential for belief accuracy about completion than it is variation in enrollment intentions, given the relative magnitudes of the two components.

8 Implications for Application Portfolios: Ranking Reversals Under Corrected Beliefs

The preceding analysis documents large forecast errors in applicants' beliefs over the admission–enrollment–completion pipeline and shows where these errors enter: mistakes about admission chances versus take-up conditional on an offer, and mistakes about persistence conditional on enrollment. This section builds on those decompositions to quantify by how much the predicted probability that the observed ranking of an applicant's top two programs would shift if the applicant's beliefs were corrected. Specifically, we compute a back-of-the-envelope partial-equilibrium implication of the forecast errors we measure by asking: holding program attributes and cutoffs fixed, how do the belief corrections implied by our estimates change the probability that an applicant ranks her 1st choice above her 2nd choice?

8.1 Belief-Based Choice Model

As before, $k = 1$ denotes the applicant's 1st-choice program and $k = 2$ the relevant 2nd-choice alternative (the design object in the main analysis). 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,

$$P_i \equiv \Pr(1_i \succ 2_i) = \frac{\exp(V_{i1})}{\exp(V_{i1}) + \exp(V_{i2})}. \tag{13}$$

Bootstrapped standard errors are clustered by applicant.

We use this model as a parsimonious mapping from reported beliefs to pairwise rankings that can be used for the belief-correction exercise, not as a full structural utility model of program choice. A natural benchmark is to let V_{ik} depend only on expected completion, $\omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1)$. This is behaviorally restrictive because applicants may value being admitted to a program, or enrolling in it if admitted, for reasons not fully captured by eventual completion (e.g., option value, timing, location, field- and/or institution-specific preferences, or other consumption components of college attendance). We therefore use a more flexible belief-based index that allows the three-stage beliefs to matter separately and through interactions.

Specifically, we specify,

$$V_{ik} = \beta_1\omega_{ik} + \beta_2\varepsilon_{ik}(1) + \beta_3\chi_{ik}(1) + \beta_4\omega_{ik}\varepsilon_{ik}(1) + \beta_5\varepsilon_{ik}(1)\chi_{ik}(1) + \beta_6\omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1) + x_{ik}'\gamma, \tag{14}$$

where ω_{ik} is the admission belief, $\varepsilon_{ik}(1)$ is the enroll-if-admitted belief, and $\chi_{ik}(1)$ is the complete-if-enroll belief.[30] The vector x_{ik} allows other factors to affect pairwise rankings. In the baseline specification, x_{ik} is empty. We then augment (14) with field and institution dummies and distance controls (km from the applicant's municipality to the program's municipality and a dummy if they are in the same municipality), and finally also with additional elicited beliefs that may affect program rankings through channels not captured by the admission–enrollment–completion beliefs (i.e., expected average GPA in the program, relative ability rank in the program, and earnings in the 1st job and at age 45). These richer specifications are intended to make the implied reversal calculations less sensitive to restrictive preference assumptions, not to provide a complete model of program choice.

8.2 *Belief Corrections*

We construct corrected beliefs by adding to the reported beliefs the corresponding estimated mean forecast errors from Section 7. (Recall that forecast errors are defined as realizations minus expectations.) We apply constant, stage-specific shifts separately for $k = 1$ and $k = 2$, for the same sample as in the main validation analysis. Corrected probabilities are truncated to the unit interval.

[30] A natural benchmark would restrict V_{ik} to depend only on expected completion, $\omega_{ik}\varepsilon_{ik}(1)\chi_{ik}(1)$. In our data, this restriction on (14) is strongly rejected.

Let $T(x) \equiv \min\{1, \max\{0, x\}\}$ denote truncation to $[0,1]$. For $k \in \{1,2\}$, define the corrected beliefs as,

$$\omega_{ik}^{corr} = T\left(\omega_{ik} + \widehat{FE}_k^{o}\right), \tag{15}$$

$$\varepsilon_{ik}^{corr}(1) = T\left(\varepsilon_{ik}(1) + \widehat{FE}_k^{\Delta^e}\right), \tag{16}$$

$$\chi_{ik}^{corr}(1) = T\left(\chi_{ik}(1) + \widehat{FE}_k^{\Delta^c}\right), \tag{17}$$

where $\widehat{FE}_k^{o}$ is the estimated mean forecast error in admission beliefs, $\widehat{FE}_k^{\Delta^e}$ in enroll-if-admitted beliefs (the enrollment "return" FE), and $\widehat{FE}_k^{\Delta^c}$ in complete-if-enrolled beliefs (the completion return or persistence FE).

We consider three component-wise corrections that map directly to the decompositions in Section 3, as follows:

(a) *System correction:* replace ω_{ik} by ω_{ik}^{corr} and leave $\varepsilon_{ik}(1)$ and $\chi_{ik}(1)$ unchanged.

(b) *Personal correction (take-up):* replace $\varepsilon_{ik}(1)$ by $\varepsilon_{ik}^{corr}(1)$ and leave ω_{ik} and $\chi_{ik}(1)$ unchanged.

(c) *Persistence correction:* replace $\chi_{ik}(1)$ by $\chi_{ik}^{corr}(1)$ and leave ω_{ik} and $\varepsilon_{ik}(1)$ unchanged.

We also consider a *full correction* that applies all three corrections simultaneously.

8.3 Implied Ranking Reversals

Given a correction scenario, we form corrected deterministic utility indices by replacing the relevant belief components in (14) with their corrected counterparts, holding the estimated coefficients fixed. Let

$$\widehat{P}_i^{base} = \frac{\exp(\widehat{V}_{i1}^{base})}{\exp(\widehat{V}_{i1}^{base}) + \exp(\widehat{V}_{i2}^{base})}, \qquad \widehat{P}_i^{corr} = \frac{\exp(\widehat{V}_{i1}^{corr})}{\exp(\widehat{V}_{i1}^{corr}) + \exp(\widehat{V}_{i2}^{corr})}, \tag{18}$$

denote respectively the baseline and corrected predicted probabilities that applicant i ranks her 1st-choice program ($k = 1$) above her 2nd-choice program ($k = 2$).

Table 7 reports the change in the predicted probability that an applicant ranks her 1st choice above the relevant 2nd-ranked alternative after replacing subjective beliefs with corrected beliefs, that is,

$$\Delta P_i \equiv \widehat{P}_i^{corr} - \widehat{P}_i^{base}. \tag{19}$$

Negative values indicate that the belief correction reduces the predicted probability that the applicant keeps her observed 1st choice on top (equivalently, increases the predicted

Table 7. Change in the Predicted Probability of Ranking the 1st-Choice Program First under Corrected Beliefs (percentage points)

	(1)		(2)		(3)	
Correct 1st-choice beliefs						
(a) System (Admit)	1.2	(0.0)	1.2	(0.0)	1.3	(0.0)
(b) Personal (Enroll ∣ Admit)	-1.2	(0.1)	-1.0	(0.1)	-0.9	(0.1)
(c) Persistence (Complete ∣ Enroll)	-12.9	(1.6)	-11.6	(1.7)	-15.4	(2.1)
(d) Full correction	-12.5	(1.5)	-11.0	(1.6)	-14.4	(2.0)
Correct 2nd-choice beliefs						
(a) System (Admit)	-6.1	(0.2)	-6.3	(0.3)	-6.6	(0.3)
(b) Personal (Enroll ∣ Admit)	-1.2	(0.1)	-1.0	(0.1)	-0.9	(0.1)
(c) Persistence (Complete ∣ Enroll)	-5.2	(0.6)	-4.5	(0.5)	-5.4	(0.7)
(d) Full correction	-13.1	(0.6)	-12.5	(0.6)	-13.9	(0.8)
Correct 1st- & 2nd-choice beliefs						
(a) System (Admit)	-4.8	(0.2)	-5.0	(0.2)	-5.0	(0.2)
(b) Personal (Enroll ∣ Admit)	-2.3	(0.2)	-2.0	(0.2)	-1.7	(0.2)
(c) Persistence (Complete ∣ Enroll)	-19.0	(2.7)	-17.0	(2.3)	-22.2	(2.9)
(d) Full correction	-27.1	(2.6)	-25.3	(2.4)	-31.2	(2.9)
Controls						
Institution/Field/Distance			✓		✓	
Additional beliefs					✓	
N	6,460		6,462		5,476	

Notes: Entries report the average change (corrected minus baseline) in the predicted probability that the applicant ranks her current 1st-choice program ($k = 1$) above the relevant 2nd-ranked alternative ($k = 2$) after replacing subjective beliefs with corrected beliefs. Negative entries indicate corrections that reduce the predicted probability of keeping the current 1st choice ranked first (equivalently, increase the predicted probability of switching to $k = 2$). Values are in percentage points. Standard errors (in parentheses) are bootstrap standard errors clustered at the applicant level. Column 1 shows estimates based a on a baseline specification, using only the main beliefs (admission, enrollment given admission, and completion given enrollment) and interactions of theirs. Column 2 shows estimates based on a specification that further conditions on institution and field dummies and distance controls (km from the applicant's municipality to the program's municipality and a dummy if they are in the same municipality). Column 3 shows estimates based on a specification that further conditions on additional elicited beliefs (i.e., expected average GPA in the program, relative ability rank in the program, and earnings in 1st job and at age 45).

probability of switching to her observed 2nd choice). To connect this exercise to the decomposition results in Section 7, we report these averages separately for each component-wise correction and for the full correction.

Under the joint correction of both $k = 1$ and $k = 2$ beliefs, the full correction implies a large change in predicted top-two ordering in all three specifications. This robustness is important because the pairwise choice model used in this exercise is necessarily restrictive. Programs are highly fine-grained, so the specification cannot absorb arbitrary program-level heterogeneity (e.g., saturated program fixed effects) or rich interactions between program attributes and applicant heterogeneity without creating very small cells. Columns (2) and (3) therefore provide robustness checks, as they add progressively richer controls for institution/field/distance and for other elicited beliefs (grades, peer rank, and earnings). The main conclusions are stable across these specifications.

The component-wise corrections line up with the decomposition results in the main analysis. In the joint correction of $k = 1$ and $k = 2$ beliefs, the persistence component (complete-if-enrolled beliefs) is by far the largest in every specification (about 17–22 percentage points in absolute value). The system component (offer beliefs) is economically meaningful but much smaller (about 5 percentage points), and the personal take-up component (enroll-if-admitted beliefs) is smaller still (about 2 percentage points). The full correction is correspondingly large (about 25–31 percentage points). Thus, the same forecast errors that dominate the completion decompositions account for most of the implied change in the ranking of the two most relevant options at the admissions margin.

The table also shows where the implied ranking changes come from. Correcting $k = 1$ beliefs only yields a large effect through persistence beliefs, while the system correction is positive. This sign implies that correcting 1st-choice offer beliefs in isolation increases the predicted probability of keeping the current 1st choice on top. Correcting $k = 2$ beliefs only reduces the predicted probability of keeping $k = 1$ on top through all three components, with the system correction especially important. The strongest sign asymmetry is therefore in admission beliefs: correcting $k = 1$ admission beliefs moves predicted ordering toward keeping the current 1st choice, whereas correcting $k = 2$ admission beliefs moves predicted ordering away from it. These asymmetries match the decomposition evidence: forecast errors differ across the two offer states, and the implied ranking effects reflect those state-specific errors.

More generally, the pattern in Table 7 shows that forecast errors accumulate along the admission–enrollment–completion sequence. Errors at earlier stages affect beliefs about downstream outcomes mechanically, and errors in persistence add further distortion at the completion stage. The full correction therefore combines mistakes that enter at different points in the sequence rather than reflecting a single forecasting mistake. (Because the choice index is nonlinear and probabilities are bounded, the full-correction effect need not equal the sum of the component-wise effects exactly.)

These estimates are partial-equilibrium implications. They quantify how correcting applicants' beliefs changes the predicted ordering of the two most relevant options at the local admissions margin, holding program attributes, cutoffs, and the broader allocation environment fixed. They do not incorporate equilibrium feedback through changes in applicants' full application portfolios or through the centralized assignment mechanism. Within that fixed-environment comparison, however, the estimated effects are large and show that the forecast errors documented in the main analysis are consequential for how applicants rank programs.

9 Conclusion

This paper studies beliefs and realized outcomes in a centralized, cutoff-based higher-education admissions system. We elicit applicants' expectations about receiving offers, enrolling, and completing their 1st- and 2nd-choice programs, and we link these survey measures to administrative records on realized offers and subsequent educational choices. Quasi-random variation around admission cutoffs identifies objective causal effects at the policy-relevant admission margin, while the survey provides subjective, *ex ante* counterparts defined over the same contingencies. Our framework clarifies which subjective and objective objects are comparable for marginal applicants and provides decompositions that locate where forecast errors enter along the admission–enrollment–completion sequence.

Our main empirical focus is a two-sided counterfactual for marginal applicants whose relevant fallback from missing a first-choice offer is receiving an offer from their second-choice program. In this group, the objective first-minus-second differences are positive for enrollment and for completion per offer. Applicants perceive first-minus-second differences with the same sign on these offer-contingent margins, and the perceived and objective first-minus-second difference in completion conditional on enrollment is of comparable magnitude. The central forecasting error is therefore not primarily in the first-minus-second contrast, but in levels: applicants substantially overstate completion under both offer states, especially completion conditional on enrollment.

The decompositions locate where these errors arise. For enrollment, forecast errors in unconditional enrollment are driven mainly by beliefs about offer probabilities, while errors in take-up conditional on an offer are smaller and often offset errors about the offer process. This structure is especially important for second priorities, where pessimism about receiving a second-choice offer is quantitatively large. For completion, forecast errors in unconditional completion are dominated by persistence: beliefs about completing conditional on enrollment are systematically too high for both first- and second-choice programs. Errors in enrollment intentions matter little for first-choice completion and are more relevant for second-choice completion, where they can partially offset persistence overoptimism in unconditional completion near the cutoff.

Heterogeneity is concentrated in the same components. Differences across applicant backgrounds are most evident in beliefs about offer probabilities and in beliefs about persistence, with less systematic variation in take-up conditional on an offer. Prior achievement is associated with less pessimism about admission and less optimism about completion conditional on enrollment, while prior application experience does not systematically attenuate persistence overoptimism at the admission margin. Persistence overoptimism remains widespread.

We also show that these forecast errors are consequential for applicants' portfolios. In a partial-equilibrium pairwise-choice exercise for the first- versus second-choice ranking, replacing subjective beliefs with corrected beliefs produces large changes in the predicted probability that applicants keep their current first choice ranked first, and most of the full-correction effect is accounted for by forecast errors in beliefs about completion conditional on enrollment. Forecast errors that enter late in the offer--enroll--complete sequence can therefore generate large distortions in application behavior.

Taken together, our results disentangle three margins that are often bundled in discussions of education choice under uncertainty: beliefs about the admissions system (program admission probabilities), beliefs about personal choice (program take-up conditional on an offer), and beliefs about persistence (program completion given enrollment). Applicants are relatively accurate about take-up at their top priority, but they misperceive the offer process---especially at lower priorities---and they overstate persistence once enrolled. These patterns imply that, even in centralized systems with strong incentive properties, the mapping from offers to completed schooling can be misunderstood in ways that are consequential for submitted rankings, for the interpretation of causal effects at admission cutoffs, and for the design of applicant-facing information. A natural next step is to evaluate which forms of credible, targeted information---about admission chances and program-specific persistence and completion risks---would improve application decisions the most and whether such improvements would differentially benefit applicants with weaker information or preparation.

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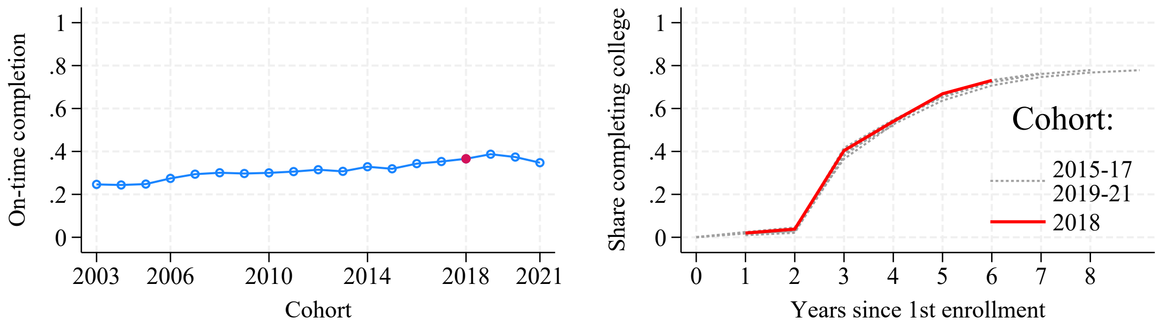
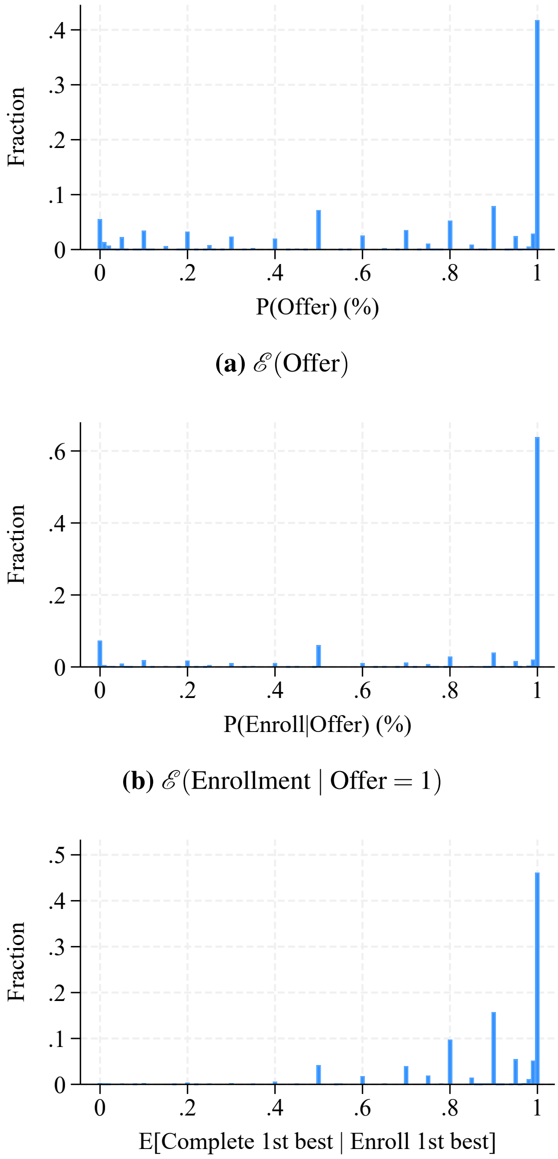
A Extra Figures



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

(b) Completion by year since 1st enrollment, 2016-2021 cohorts

Figure A1. Across cohort comparison of college completion



(a) $\mathscr{E}(\text{Offer})$

(b) $\mathscr{E}(\text{Enrollment} \mid \text{Offer} = 1)$

(c) $\mathscr{E}(\text{Completion} \mid \text{Enrollment} = 1)$

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

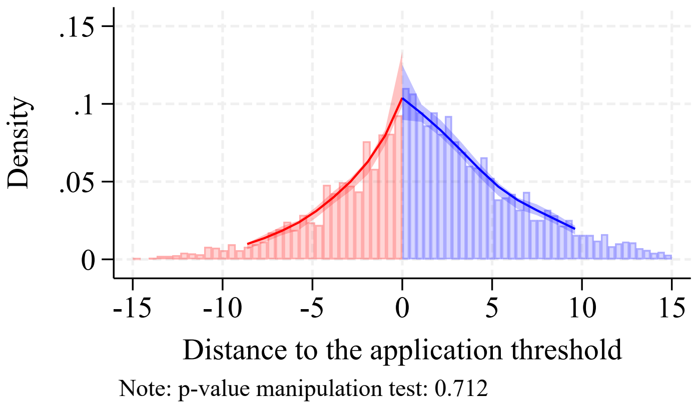
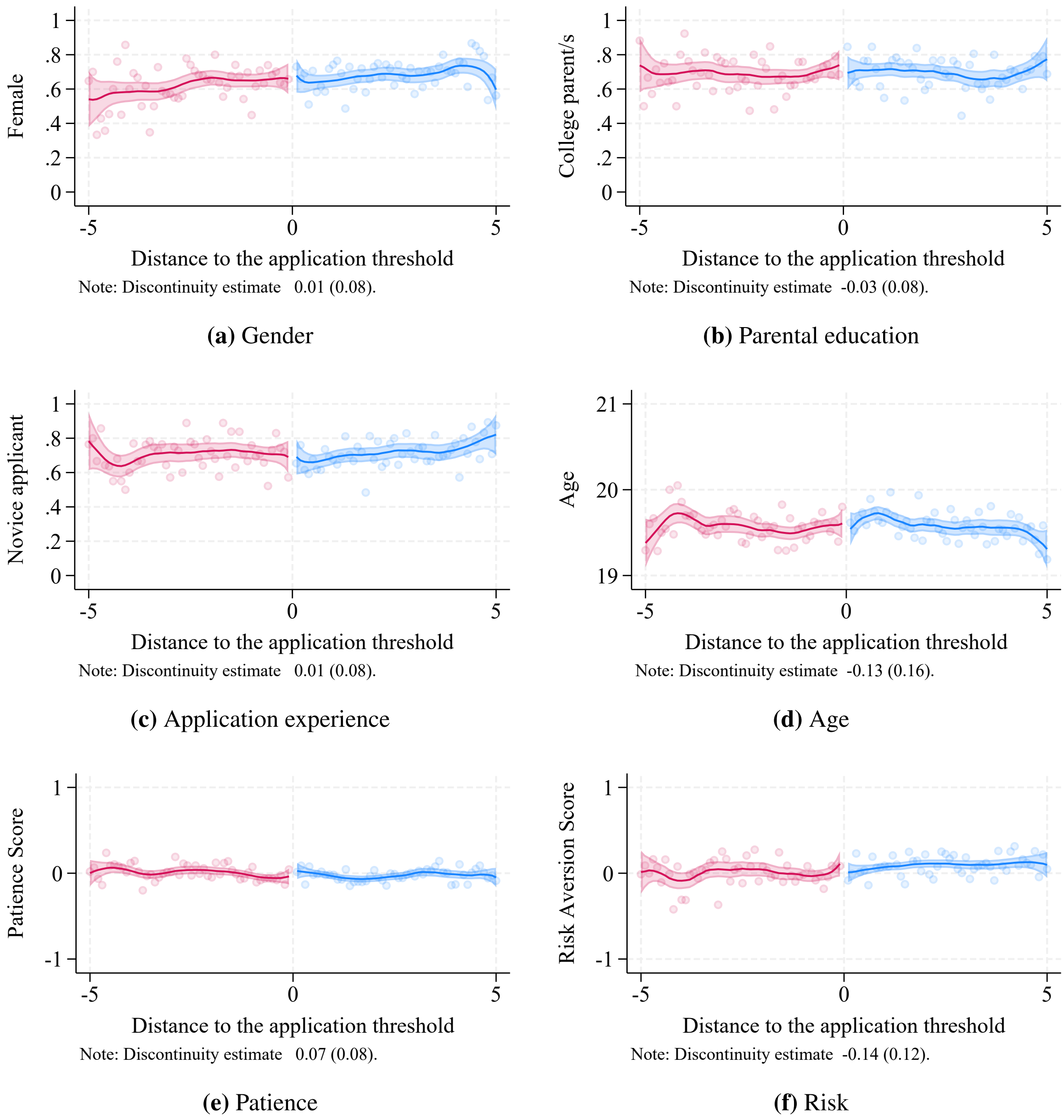


Figure A3. Bunching Test for Manipulation around the Admission Margin



(a) Gender

(b) Parental education

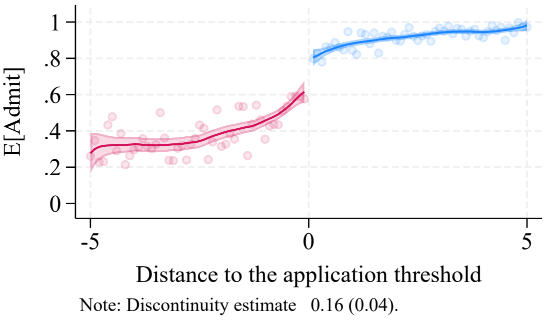
(c) Application experience

(d) Age

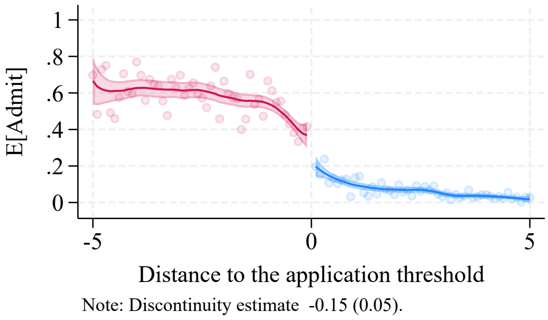
(e) Patience

(f) Risk

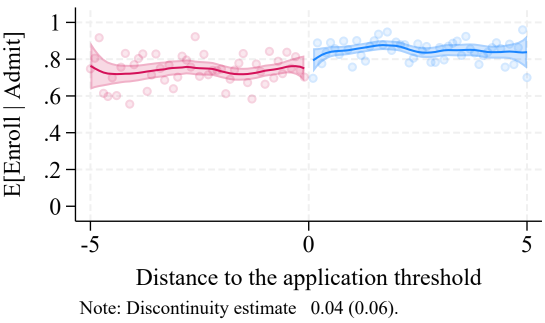
Figure A4. Balancing of Predetermined Characteristics



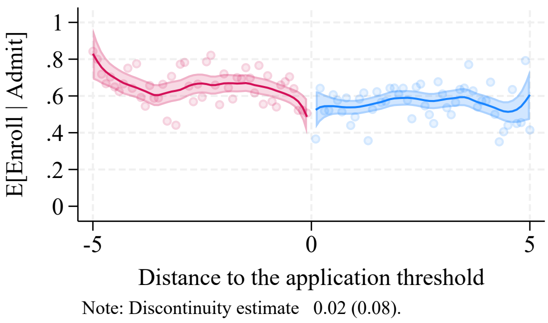
(a) $\mathscr{E}$[Admission], first choice



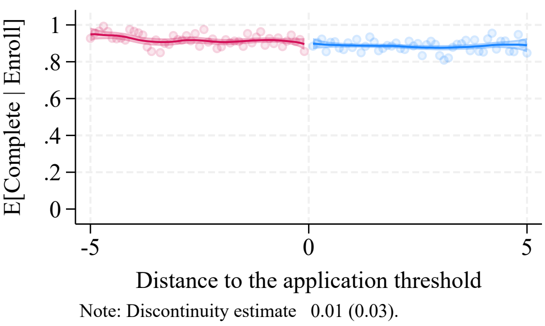
(b) $\mathscr{E}$[Admission], second choice



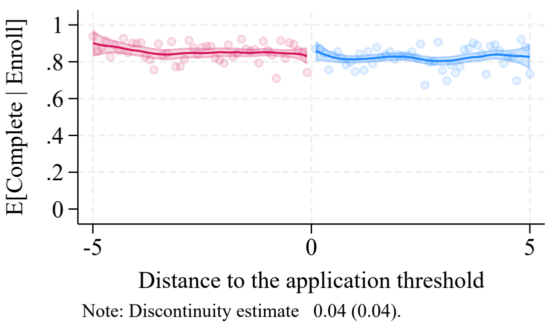
(c) $\mathscr{E}$[Enrollment | Admission], first choice



(d) $\mathscr{E}$[Enrollment | Admission], second choice

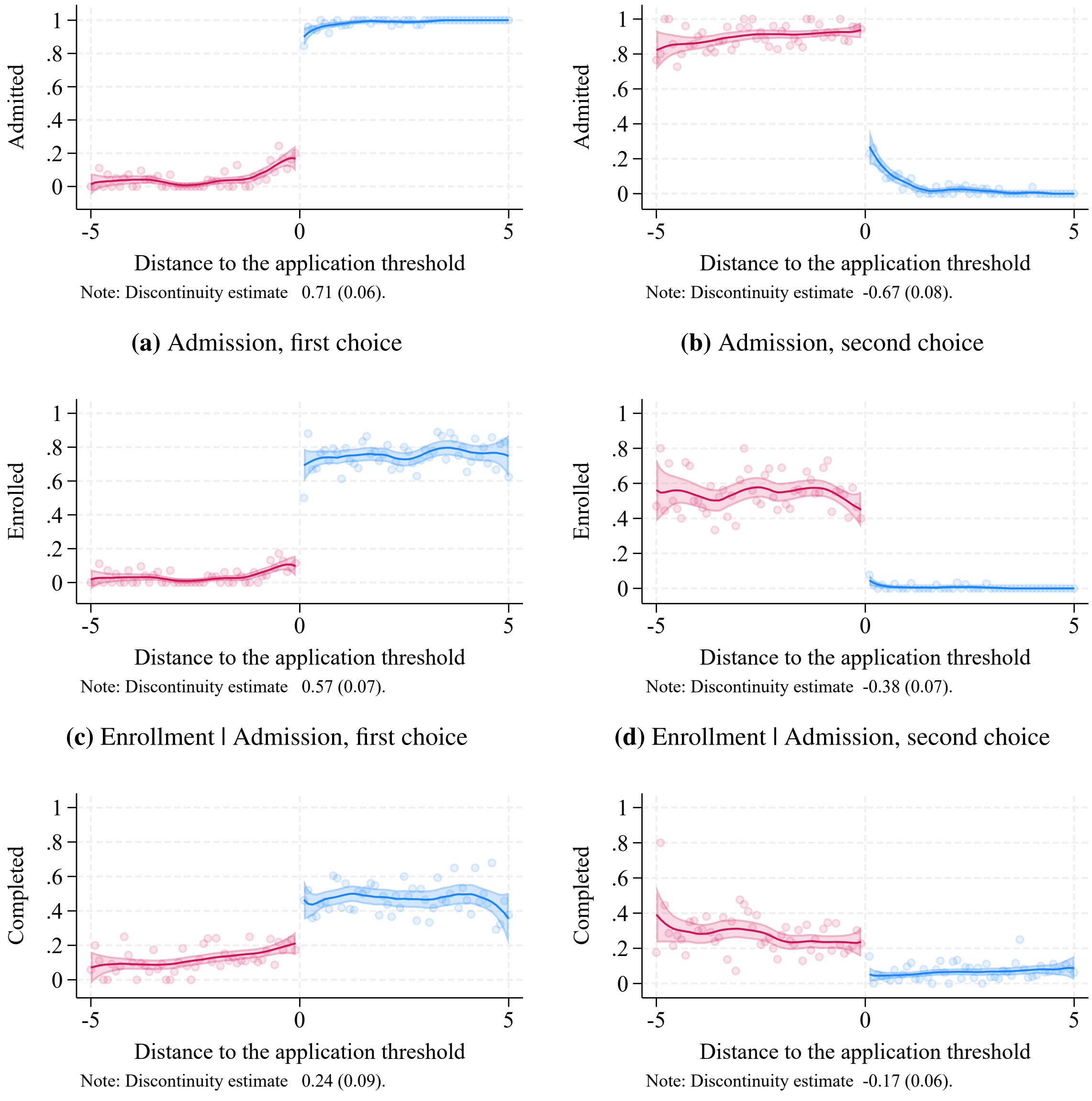


(e) $\mathscr{E}$[Completion | Enrollment], first choice



(f) $\mathscr{E}$[Completion | Enrollment], second choice

Figure A5. Balancing of Subjective Expectations (predetermined)



(a) Admission, first choice

(b) Admission, second choice

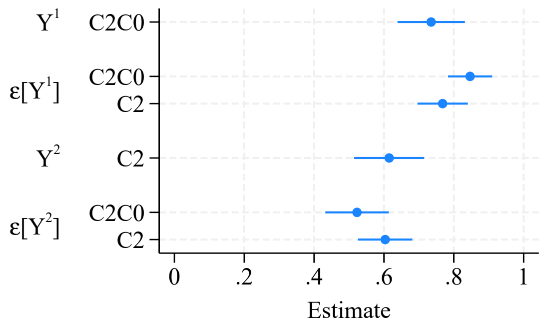
(c) Enrollment | Admission, first choice

(d) Enrollment | Admission, second choice

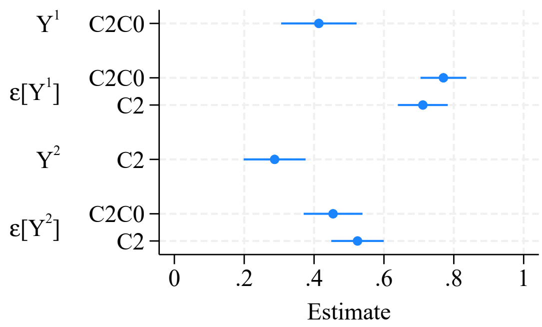
(e) Completion | Enrollment, first choice

(f) Completion | Enrollment, second choice

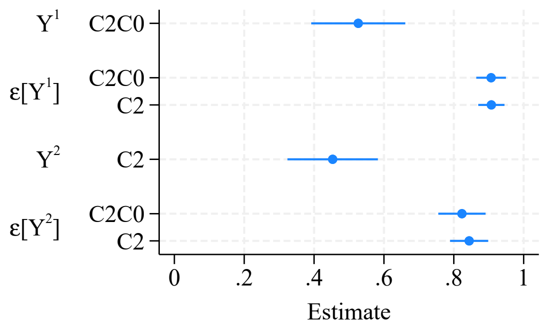
Figure A6. Admission, Enrollment, and Completion Discontinuities (Actual)



(a) Enroll(Offer)



(b) Complete(Offer)



(c) Complete(Enroll)

Figure A7. Objective vs Subjective Potential Outcomes and Causal Effects of 1st vs 2nd Choice among Marginal Applicants

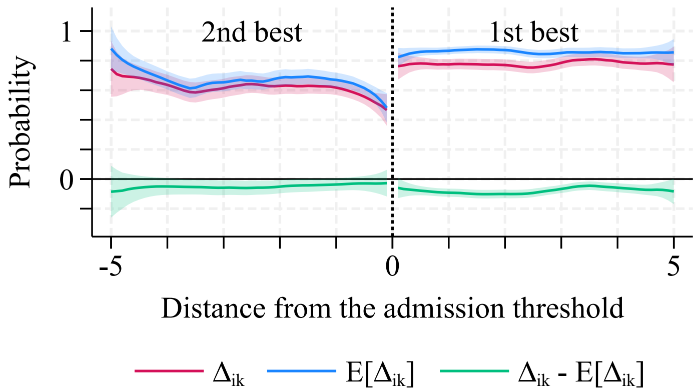


Figure A8. Enrollment Return to Admission: Avg(Δ_{ik}), Avg($\mathscr{E}[\Delta_{ik}]$), and Avg($\Delta_{ik} - \mathscr{E}[\Delta_{ik}]$) by Distance from the Admission Margin

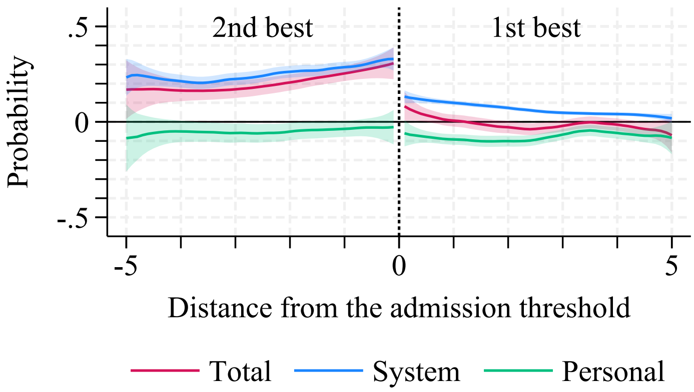


Figure A9. Enrollment Forecast Error: Decomposition into Personal (Enroll | Admit) and System (Admit) Components by Distance from the Admission Margin – All Treated

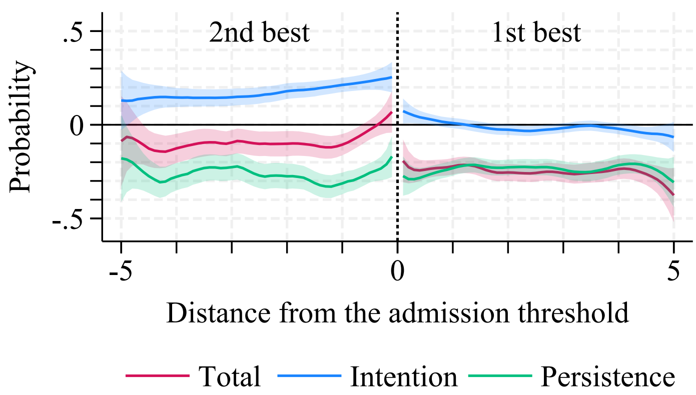


Figure A10. Completion Forecast Error: Decomposition into Intention (Enroll) and Persistence (Complete | Enroll) Components by Distance from the Admission Margin – All Treated

B Extra Tables

Table A1. Admission Statistics

	Unconditional (All) (1)	**Conditional on Receiving Any Offer** (2)	**Conditional on Not Receiving an Offer for 1st Choice** (3)
Percent admitted to...			
1st choice	62.8	63.5	-
2nd choice	33.1	33.5	91.8
> 2nd choice	2.9	3.0	8.2
No program	1.2	-	-
N	4,138	4,091	1,497

Table A2. Covariate Balance Tests around the Admission Margin

	Estimate (1)	**Std. Error** (2)	**p-value** (3)
Female	0.01	0.08	0.928
College educated parent/s	-0.03	0.08	0.713
Age	-0.13	0.16	0.420
First-time applicant	0.01	0.08	0.887
Ability (Application score)	-0.55	1.46	0.705
Patience Score	0.07	0.08	0.394
Risk Aversion Score	-0.14	0.12	0.278
E[Admitted first choice]	0.16	0.04	<.001
E[Enroll first choice | Admitted first choice]	0.04	0.06	0.467
E[Complete first choice | Enroll first choice]	0.01	0.03	0.746

Table A3. Applicants' Characteristics by Group: Marginal (Compliers), All Treated, and All Applicants

	Marginal Applicants				**All Treated**		**All Applicants**
	(1)		(2)		(3)		(4)
Female	0.54	(0.05)	0.54	(0.06)	0.69	(0.01)	0.68
Age	20.0	(0.09)	19.5	(0.23)	19.7	(0.02)	19.6
First-time applicant	0.57	(0.06)	0.58	(0.07)	0.64	(0.01)	0.63
Has college-educated parent/s (at least one)	0.77	(0.05)	0.71	(0.06)	0.71	(0.01)	0.69
Ability (application score)	49.4	(0.74)	49.4	(1.28)	50.5	(0.14)	50.6
Risk tolerance & competitiveness score (normalized)	0.01	(0.06)	0.04	(0.04)	0.12	(0.01)	0
Time patience score (normalized)	0.04	(0.05)	-0.01	(0.03)	-0.03	(0.01)	0
Field of Study:							
- Social Science & Humanities	0.21	(0.04)	0.21	(0.03)	0.17	(0.01)	0.18
- Science & Engineering	0.26	(0.05)	0.25	(0.04)	0.23	(0.01)	0.23
- Law & Business	0.25	(0.04)	0.25	(0.04)	0.17	(0.01)	0.17
- Teaching	0.07	(0.03)	0.06	(0.02)	0.12	(0.01)	0.11
- Health	0.21	(0.06)	0.22	(0.06)	0.31	(0.01)	0.31
Estimator	2SLS		Non-par.				
Group Size	2,412				2,156		1

Table A4. Potential Outcomes for 1st and 2nd Choice Programs among Marginal Applicants - Enroll(Offer)

	Complier Share	y^1	$\mathscr{E}[y^1]$	y^2	$\mathscr{E}[y^2]$
A. Unbalanced Sample					
C2C0	0.77	0.75	0.85		0.52
	(0.019)	(0.047)	(0.030)		(0.046)
C2	0.75		0.76	0.56	0.60
	(0.025)		(0.032)	(0.044)	(0.040)
C0	0.03		0.35		0.30
	(0.018)		(0.310)		(0.315)
A1	0.18	0.65	0.89		0.58
	(0.012)	(0.032)	(0.016)		(0.032)
A2	0.18		0.77	0.11	0.56
	(0.011)		(0.021)	(0.023)	(0.030)
N	2,869	2,869	2,869	2,869	2,234
B. Balanced Sample					
C2C0	0.79	0.74	0.85		0.52
	(0.020)	(0.049)	(0.032)		(0.046)
C2	0.76		0.77	0.61	0.60
	(0.028)		(0.037)	(0.051)	(0.040)
C0	0.03		0.51		0.30
	(0.020)		(0.335)		(0.315)
A1	0.15	0.71	0.87		0.58
	(0.012)	(0.037)	(0.021)		(0.032)
A2	0.19		0.74	0.11	0.56
	(0.013)		(0.024)	(0.025)	(0.030)
N	2,234	2,234	2,234	2,234	2,234

Note: Estimates obtained using the linear 2SLS procedures described in the text. Panel A reports the unbalanced sample and Panel B the sample balanced across outcomes.

Table A5. Potential Outcomes for 1st and 2nd Choice Programs among Marginal Applicants - Complete(Offer)

	Complier Share	y^1	$\mathscr{E}[y^1]$	y^2	$\mathscr{E}[y^2]$
A. Unbalanced sample					
C2C0	0.77	0.45	0.78		0.45
	(0.019)	(0.052)	(0.031)		(0.043)
C2	0.75		0.70	0.26	0.52
	(0.025)		(0.031)	(0.039)	(0.038)
C0	0.03		0.36		0.34
	(0.018)		(0.289)		(0.288)
A1	0.18	0.50	0.83		0.49
	(0.012)	(0.035)	(0.018)		(0.031)
A2	0.18		0.69	0.04	0.49
	(0.011)		(0.022)	(0.019)	(0.029)
N	2,869	2,869	2,869	2,869	2,234
B. Balanced sample					
C2C0	0.79	0.41	0.77		0.45
	(0.020)	(0.055)	(0.033)		(0.043)
C2	0.76		0.71	0.28	0.52
	(0.028)		(0.036)	(0.045)	(0.038)
C0	0.03		0.52		0.34
	(0.020)		(0.318)		(0.288)
A1	0.15	0.53	0.80		0.49
	(0.012)	(0.041)	(0.022)		(0.031)
A2	0.19		0.64	0.06	0.49
	(0.013)		(0.025)	(0.022)	(0.029)
N	2,234	2,234	2,234	2,234	2,234

Note: Estimates obtained using the linear 2SLS procedures described in the text. Panel A reports the unbalanced sample and Panel B the sample balanced across outcomes.

Table A6. Potential Outcomes for 1st and 2nd Choice Programs among Marginal Applicants - Complete(Enroll)

	Complier Share	y^1	$\mathscr{E}[y^1]$	y^2	$\mathscr{E}[y^2]$
A. Unbalanced sample					
C2C0	0.55	0.55	0.90		0.82
	(0.041)	(0.061)	(0.020)		(0.035)
C2	0.40		0.91	0.48	0.84
	(0.039)		(0.019)	(0.064)	(0.028)
C0	0.16		0.94		0.88
	(0.049)		(0.072)		(0.155)
A1	0.15	0.72	0.95		0.84
	(0.014)	(0.044)	(0.009)		(0.021)
A2	0.04		0.94	0.52	0.84
	(0.013)		(0.054)	(0.159)	(0.089)
N	2,869	2,869	2,869	2,869	2,234
B. Balanced sample					
C2C0	0.54	0.53	0.91		0.82
	(0.044)	(0.069)	(0.022)		(0.035)
C2	0.44		0.91	0.45	0.84
	(0.044)		(0.019)	(0.066)	(0.028)
C0	0.11		0.97		0.88
	(0.055)		(0.129)		(0.155)
A1	0.15	0.72	0.94		0.84
	(0.014)	(0.046)	(0.008)		(0.021)
A2	0.04		0.95	0.73	0.84
	(0.015)		(0.065)	(0.182)	(0.089)
N	2,234	2,234	2,234	2,234	2,234

Note: Estimates obtained using the linear 2SLS procedures described in the text. Panel A reports the unbalanced sample and Panel B the sample balanced across outcomes.

Table A7. Enrollment Return to Admission: Actual, Expected, and Forecast Error

	Marginal Applicants				All Treated	
	(1)		(2)		(3)	
1st-choice program (k=1)						
(a) Actual (Δ^e_{i1})	0.80	(0.042)	0.80	(0.050)	0.78	(0.008)
(b) Expected ($\mathscr{E}_i[\Delta^e_{i1}]$)	0.85	(0.028)	0.83	(0.038)	0.85	(0.006)
(c) Forecast Error ($FE^{\Delta^e}_{i1}$)	-0.05	(0.033)	-0.05	(0.029)	-0.08	(0.006)
N	2,869		2,869		2,594	
2nd-choice program (k=2)						
(a) Actual (Δ^e_{i2})	0.70	(0.059)	0.65	(0.058)	0.60	(0.014)
(b) Expected ($\mathscr{E}_i[\Delta^e_{i2}]$)	0.60	(0.046)	0.54	(0.049)	0.65	(0.011)
(c) Forecast Error ($FE^{\Delta^e}_{i2}$)	0.10	(0.057)	0.09	(0.053)	-0.05	(0.013)
N	2,234		2,234		1,250	
Estimator	2SLS		Non-par.			

Note: For each program, (c) = (a) - (b). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS) in Col. (1) and bias-corrected local-linear regression with MSE-optimal bandwidths, based on Kolesár and Rothe (2018)'s nonparametric `rdhonest`, in Col. (2). Robust standard errors are shown in parentheses next to the point estimates.

Table A8. Enrollment Forecast Error: Decomposition by Gender and of the Gender Gap

	All Treated			Marginal Applicants		
	Female (1)	Male (2)	Gap (1-2) (3)	Female (4)	Male (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) System: Admit	0.086	0.069	0.017	0.104	0.069	0.035
	(0.005)	(0.007)	(0.008)	(0.024)	(0.023)	(0.025)
(b) Personal: Enroll | Admit	-0.068	-0.120	0.052	-0.050	-0.054	0.004
	(0.009)	(0.015)	(0.018)	(0.035)	(0.049)	(0.050)
(c) Total FE: Enroll (uncond.)	0.017	-0.051	0.068	0.053	0.014	0.039
	(0.009)	(0.017)	(0.019)	(0.037)	(0.053)	(0.055)
2nd-choice program (k=2)						
(a) System: Admit	0.258	0.287	-0.030	0.332	0.333	-0.001
	(0.011)	(0.016)	(0.019)	(0.056)	(0.077)	(0.114)
(b) Personal: Enroll | Admit	-0.051	-0.093	0.042	0.141	0.015	0.126
	(0.019)	(0.025)	(0.031)	(0.105)	(0.148)	(0.223)
(c) Total FE: Enroll (uncond.)	0.207	0.194	0.012	0.473	0.347	0.125
	(0.019)	(0.026)	(0.032)	(0.088)	(0.127)	(0.180)

Note: (a) System: Admit ($FE^o_{ik}\varepsilon_{ik}(1)$) + (b) Personal: Enroll | Admit ($o_{ik}FE^{\Delta^e}_{ik}$) = (c) Total FE: Enroll (uncond., FE^e_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below to the point estimates.

Table A9. Completion Forecast Error: Decomposition by Gender and of the Gender Gap

	All Treated			Marginal Applicants		
	Female	Male	Gap (1-2)	Female	Male	Gap (4-5)
	(1)	(2)	(3)	(4)	(5)	(6)
1st-choice program (k=1)						
(a) Intention: Enroll	0.016	-0.048	0.064	0.048	0.013	0.036
	(0.008)	(0.015)	(0.017)	(0.034)	(0.046)	(0.047)
(b) Persistence: Complete ∣ Enroll	-0.248	-0.215	-0.034	-0.273	-0.310	0.036
	(0.014)	(0.020)	(0.025)	(0.055)	(0.070)	(0.079)
(c) Total FE: Complete (uncond.)	-0.232	-0.262	0.030	-0.225	-0.297	0.072
	(0.015)	(0.023)	(0.027)	(0.058)	(0.078)	(0.084)
2nd-choice program (k=2)						
(a) Intention: Enroll	0.175	0.165	0.010	0.394	0.277	0.118
	(0.017)	(0.022)	(0.028)	(0.075)	(0.110)	(0.154)
(b) Persistence: Complete ∣ Enroll	-0.247	-0.267	0.020	-0.342	-0.245	-0.097
	(0.019)	(0.025)	(0.031)	(0.060)	(0.077)	(0.090)
(c) Total FE: Complete (uncond.)	-0.072	-0.102	0.029	0.052	0.031	0.020
	(0.020)	(0.026)	(0.032)	(0.061)	(0.080)	(0.096)

Note: (a) Intention: Enroll ($\chi_{ik}(1)FE^{e}_{ik}$) + (b) Persistence: Complete ∣ Enroll ($FE^{\Delta^c}_{ik} e_{ik}$) = (c) Total FE: Complete (uncond., FE^{c}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below the point estimates.

Table A10. Enrollment Forecast Error: Decomposition by Parental Education and of the Parental Education Gap

	All Treated			**Marginal Applicants**		
	College (1)	No College (2)	Gap (1-2) (3)	College (4)	No College (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) System: Admit	0.073	0.097	-0.025	0.073	0.130	-0.056
	(0.004)	(0.008)	(0.009)	(0.021)	(0.034)	(0.032)
(b) Personal: Enroll ∣ Admit	-0.093	-0.065	-0.029	-0.060	-0.035	-0.026
	(0.009)	(0.014)	(0.017)	(0.036)	(0.047)	(0.048)
(c) Total FE: Enroll (uncond.)	-0.021	0.032	-0.053	0.013	0.095	-0.082
	(0.010)	(0.015)	(0.018)	(0.040)	(0.048)	(0.051)
2nd-choice program (k=2)						
(a) System: Admit	0.251	0.309	-0.058	0.302	0.413	-0.111
	(0.011)	(0.017)	(0.020)	(0.050)	(0.091)	(0.123)
(b) Personal: Enroll ∣ Admit	-0.071	-0.056	-0.016	0.203	-0.208	0.410
	(0.018)	(0.028)	(0.033)	(0.083)	(0.158)	(0.205)
(c) Total FE: Enroll (uncond.)	0.180	0.254	-0.074	0.504	0.205	0.299
	(0.018)	(0.030)	(0.035)	(0.068)	(0.125)	(0.150)

Note: (a) System: Admit ($FE^{o}_{ik}\varepsilon_{ik}(1)$) + (b) Personal: Enroll ∣ Admit ($o_{ik}FE^{\Delta^e}_{ik}$) = (c) Total FE: Enroll (uncond., FE^{e}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below to the point estimates.

Table A11. Completion Forecast Errors: Decomposition by Parental Education and of the Parental Education Gap

	All Treated			Marginal Applicants		
	College (1)	No College (2)	Gap (1-2) (3)	College (4)	No College (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) Intention: Enroll	-0.019	0.028	-0.047	0.012	0.085	-0.074
	(0.009)	(0.014)	(0.016)	(0.035)	(0.044)	(0.046)
(b) Persistence: Complete | Enroll	-0.241	-0.229	-0.012	-0.288	-0.280	-0.008
	(0.014)	(0.021)	(0.025)	(0.054)	(0.074)	(0.080)
(c) Total FE: Complete (uncond.)	-0.260	-0.201	-0.059	-0.276	-0.195	-0.082
	(0.015)	(0.023)	(0.027)	(0.058)	(0.079)	(0.085)
2nd-choice program (k=2)						
(a) Intention: Enroll	0.148	0.225	-0.077	0.415	0.164	0.251
	(0.016)	(0.027)	(0.031)	(0.059)	(0.109)	(0.130)
(b) Persistence: Complete | Enroll	-0.244	-0.279	0.035	-0.348	-0.181	-0.166
	(0.017)	(0.029)	(0.034)	(0.056)	(0.075)	(0.082)
(c) Total FE: Complete (uncond.)	-0.096	-0.054	-0.042	0.068	-0.017	0.085
	(0.018)	(0.030)	(0.035)	(0.057)	(0.079)	(0.086)

Note: (a) Intention: Enroll ($\chi_{ik}(1)FE^{e}_{ik}$) + (b) Persistence: Complete | Enroll ($FE^{\Delta^c}_{ik}e_{ik}$) = (c) Total FE: Complete (uncond., FE^{c}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below the point estimates.

Table A12. Enrollment Forecast Error: Decomposition by Application Experience and of the Application Experience Gap

	All Treated			Marginal Applicants		
	Novice	Experienced	Gap (1-2)	Novice	Experienced	Gap (4-5)
	(1)	(2)	(3)	(4)	(5)	(6)
1st-choice program (k=1)						
(a) System: Admit	0.081	0.079	0.001	0.080	0.102	-0.021
	(0.005)	(0.007)	(0.008)	(0.020)	(0.030)	(0.028)
(b) Personal: Enroll | Admit	-0.103	-0.054	-0.049	-0.093	-0.004	-0.089
	(0.010)	(0.012)	(0.016)	(0.038)	(0.041)	(0.045)
(c) Total FE: Enroll (uncond.)	-0.022	0.025	-0.048	-0.012	0.098	-0.110
	(0.011)	(0.014)	(0.017)	(0.042)	(0.044)	(0.049)
2nd-choice program (k=2)						
(a) System: Admit	0.269	0.268	0.000	0.333	0.330	0.002
	(0.011)	(0.017)	(0.020)	(0.058)	(0.081)	(0.122)
(b) Personal: Enroll | Admit	-0.099	-0.013	-0.086	0.059	0.140	-0.081
	(0.018)	(0.026)	(0.031)	(0.114)	(0.156)	(0.244)
(c) Total FE: Enroll (uncond.)	0.170	0.256	-0.086	0.392	0.471	-0.079
	(0.019)	(0.027)	(0.033)	(0.109)	(0.139)	(0.220)

Note: (a) System: Admit ($FE^{o}_{ik}\varepsilon_{ik}(1)$) + (b) Personal: Enroll | Admit ($o_{ik}FE^{\Delta^e}_{ik}$) = (c) Total FE: Enroll (uncond., FE^{e}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below to the point estimates.

Table A13. Completion Forecast Error: Decomposition by Application Experience and of the Application Experience Gap

	All Treated			Marginal Applicants		
	Novice (1)	Experienced (2)	Gap (1-2) (3)	Novice (4)	Experienced (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) Intention: Enroll	-0.020	0.020	-0.040	-0.010	0.086	-0.096
	(0.009)	(0.012)	(0.015)	(0.037)	(0.039)	(0.043)
(b) Persistence: Complete ∣ Enroll	-0.238	-0.237	-0.001	-0.215	-0.373	0.158
	(0.014)	(0.021)	(0.025)	(0.052)	(0.072)	(0.077)
(c) Total FE: Complete (uncond.)	-0.257	-0.216	-0.041	-0.225	-0.287	0.062
	(0.015)	(0.022)	(0.027)	(0.058)	(0.075)	(0.081)
2nd-choice program (k=2)						
(a) Intention: Enroll	0.150	0.207	-0.057	0.314	0.397	-0.083
	(0.017)	(0.023)	(0.028)	(0.097)	(0.122)	(0.196)
(b) Persistence: Complete ∣ Enroll	-0.249	-0.264	0.014	-0.299	-0.309	0.010
	(0.017)	(0.027)	(0.032)	(0.065)	(0.087)	(0.114)
(c) Total FE: Complete (uncond.)	-0.099	-0.057	-0.042	0.015	0.088	-0.072
	(0.018)	(0.029)	(0.034)	(0.080)	(0.094)	(0.141)

Note: (a) Intention: Enroll ($\chi_{ik}(1)FE^{e}_{ik}$) + (b) Persistence: Complete ∣ Enroll ($FE^{\Delta^c}_{ik}\, e_{ik}$) = (c) Total FE: Complete (uncond., FE^{c}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below the point estimates.

Table A14. Enrollment Forecast Error: Decomposition by Ability (GPA) and of the Ability Gap

	All Treated			Marginal Applicants		
	High (1)	Low (2)	Gap (1-2) (3)	High (4)	Low (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) System: Admit	0.062	0.115	-0.053	0.078	0.108	-0.031
	(0.004)	(0.008)	(0.009)	(0.020)	(0.032)	(0.030)
(b) Personal: Enroll | Admit	-0.096	-0.064	-0.031	-0.047	-0.070	0.022
	(0.010)	(0.013)	(0.016)	(0.036)	(0.045)	(0.047)
(c) Total FE: Enroll (uncond.)	-0.034	0.050	-0.084	0.031	0.039	-0.008
	(0.010)	(0.014)	(0.018)	(0.040)	(0.047)	(0.050)
2nd-choice program (k=2)						
(a) System: Admit	0.246	0.299	-0.052	0.296	0.442	-0.146
	(0.012)	(0.014)	(0.018)	(0.055)	(0.067)	(0.105)
(b) Personal: Enroll | Admit	-0.075	-0.056	-0.019	0.244	-0.246	0.490
	(0.019)	(0.024)	(0.031)	(0.092)	(0.118)	(0.175)
(c) Total FE: Enroll (uncond.)	0.171	0.243	-0.072	0.539	0.195	0.344
	(0.020)	(0.025)	(0.031)	(0.085)	(0.108)	(0.158)

Note: (a) System: Admit ($FE^{o}_{ik}\varepsilon_{ik}(1)$) + (b) Personal: Enroll | Admit ($o_{ik}FE^{\Delta^e}_{ik}$) = (c) Total FE: Enroll (uncond., FE^{e}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below to the point estimates.

Table A15. Completion Forecast Error: Decomposition by Ability (GPA) and of the Ability Gap

	All Treated			Marginal Applicants		
	High (1)	Low (2)	Gap (1-2) (3)	High (4)	Low (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) Intention: Enroll	-0.031	0.044	-0.075	0.030	0.028	0.002
	(0.009)	(0.013)	(0.016)	(0.036)	(0.042)	(0.044)
(b) Persistence: Complete ∣ Enroll	-0.203	-0.301	0.098	-0.271	-0.305	0.034
	(0.014)	(0.021)	(0.025)	(0.054)	(0.072)	(0.078)
(c) Total FE: Complete (uncond.)	-0.234	-0.257	0.023	-0.241	-0.277	0.036
	(0.015)	(0.022)	(0.027)	(0.058)	(0.079)	(0.084)
2nd-choice program (k=2)	0.143	0.210	-0.067	0.449	0.144	0.305
(a) Intention: Enroll	(0.017)	(0.022)	(0.028)	(0.077)	(0.098)	(0.146)
	-0.231	-0.286	0.055	-0.372	-0.159	-0.213
(b) Persistence: Complete ∣ Enroll	(0.019)	(0.024)	(0.031)	(0.066)	(0.061)	(0.085)
	-0.089	-0.076	-0.012	0.077	-0.015	0.092
(c) Total FE: Complete (uncond.)	(0.020)	(0.025)	(0.032)	(0.075)	(0.077)	(0.123)

Note: (a) Intention: Enroll ($\chi_{ik}(1) FE^{e}_{ik}$) + (b) Persistence: Complete ∣ Enroll ($FE^{\Delta^c}_{ik} e_{ik}$) = (c) Total FE: Complete (uncond., FE^{c}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below the point estimates.

Table A16. Enrollment Forecast Error: Decomposition by Patience and of the Patience Gap

	All Treated			Marginal Applicants		
	High (1)	Low (2)	Gap (1-2) (3)	High (4)	Low (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) System: Admit	0.080	0.085	-0.005	0.084	0.087	-0.003
	(0.006)	(0.007)	(0.009)	(0.027)	(0.028)	(0.029)
(b) Personal: Enroll | Admit	-0.098	-0.075	-0.023	-0.043	-0.093	0.050
	(0.012)	(0.012)	(0.017)	(0.043)	(0.044)	(0.048)
(c) Total FE: Enroll (uncond.)	-0.018	0.010	-0.028	0.041	-0.006	0.047
	(0.013)	(0.013)	(0.018)	(0.049)	(0.045)	(0.052)
2nd-choice program (k=2)						
(a) System: Admit	0.280	0.256	0.024	0.326	0.346	-0.020
	(0.014)	(0.014)	(0.020)	(0.062)	(0.078)	(0.121)
(b) Personal: Enroll | Admit	-0.093	-0.033	-0.060	0.108	0.071	0.037
	(0.022)	(0.023)	(0.032)	(0.118)	(0.142)	(0.228)
(c) Total FE: Enroll (uncond.)	0.187	0.223	-0.036	0.434	0.418	0.017
	(0.022)	(0.024)	(0.033)	(0.101)	(0.132)	(0.199)

Note: (a) System: Admit ($FE^{o}_{ik}\varepsilon_{ik}(1)$) + (b) Personal: Enroll | Admit ($o_{ik}FE^{\Delta^e}_{ik}$) = (c) Total FE: Enroll (uncond., FE^{e}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below to the point estimates.

Table A17. Completion Forecast Error: Decomposition by Patience and of the Patience Gap

	All Treated			Marginal Applicants		
	High (1)	Low (2)	Gap (1-2) (3)	High (4)	Low (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) Intention: Enroll	-0.017	0.006	-0.023	0.042	-0.007	0.049
	(0.012)	(0.011)	(0.016)	(0.044)	(0.041)	(0.046)
(b) Persistence: Complete | Enroll	-0.218	-0.242	0.024	-0.268	-0.298	0.030
	(0.017)	(0.018)	(0.025)	(0.067)	(0.063)	(0.079)
(c) Total FE: Complete (uncond.)	-0.236	-0.236	0.000	-0.226	-0.304	0.079
	(0.019)	(0.019)	(0.027)	(0.076)	(0.066)	(0.084)
2nd-choice program (k=2)						
(a) Intention: Enroll	0.157	0.192	-0.035	0.358	0.341	0.016
	(0.020)	(0.021)	(0.029)	(0.087)	(0.118)	(0.175)
(b) Persistence: Complete | Enroll	-0.287	-0.247	-0.040	-0.318	-0.367	0.049
	(0.022)	(0.023)	(0.032)	(0.073)	(0.087)	(0.119)
(c) Total FE: Complete (uncond.)	-0.130	-0.055	-0.075	0.040	-0.026	0.066
	(0.022)	(0.025)	(0.033)	(0.066)	(0.095)	(0.119)

Note: (a) Intention: Enroll ($\chi_{ik}(1)FE^{e}_{ik}$) + (b) Persistence: Complete | Enroll ($FE^{\Delta^c}_{ik}e_{ik}$) = (c) Total FE: Complete (uncond., FE^{c}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below the point estimates.

Table A18. Enrollment Forecast Errors: Decomposition by Risk Tolerance and of the Risk Tolerance Gap

	All Treated			Marginal Applicants		
	High (1)	Low (2)	Gap (1-2) (3)	High (4)	Low (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) System: Admit	0.078	0.086	-0.009	0.067	0.102	-0.035
	(0.006)	(0.006)	(0.009)	(0.027)	(0.027)	(0.029)
(b) Personal: Enroll ∣ Admit	-0.119	-0.063	-0.056	-0.089	-0.049	-0.040
	(0.014)	(0.010)	(0.017)	(0.047)	(0.040)	(0.049)
(c) Total FE: Enroll (uncond.)	-0.041	0.024	-0.065	-0.022	0.053	-0.075
	(0.015)	(0.012)	(0.019)	(0.049)	(0.045)	(0.053)
2nd-choice program (k=2)						
(a) System: Admit	0.268	0.269	-0.000	0.281	0.380	-0.099
	(0.014)	(0.014)	(0.020)	(0.068)	(0.067)	(0.116)
(b) Personal: Enroll ∣ Admit	-0.076	-0.052	-0.023	-0.024	0.178	-0.203
	(0.023)	(0.022)	(0.032)	(0.129)	(0.124)	(0.219)
(c) Total FE: Enroll (uncond.)	0.193	0.216	-0.024	0.256	0.558	-0.302
	(0.023)	(0.023)	(0.033)	(0.110)	(0.105)	(0.177)

Note: (a) System: Admit ($FE^{o}_{ik}\varepsilon_{ik}(1)$) + (b) Personal: Enroll ∣ Admit ($o_{ik}FE^{\Delta^e}_{ik}$) = (c) Total FE: Enroll (uncond., FE^{e}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below to the point estimates.

Table A19. Completion Forecast Errors: Decomposition by Risk Tolerance and of the Risk Tolerance Gap

	All Treated			Marginal Applicants		
	High (1)	Low (2)	Gap (1-2) (3)	High (4)	Low (5)	Gap (4-5) (6)
1st-choice program (k=1)						
(a) Intention: Enroll	-0.036	0.018	-0.054	-0.014	0.046	-0.060
	(0.013)	(0.010)	(0.017)	(0.044)	(0.040)	(0.047)
(b) Persistence: Complete ∣ Enroll	-0.243	-0.219	-0.023	-0.289	-0.279	-0.011
	(0.019)	(0.017)	(0.025)	(0.067)	(0.063)	(0.079)
(c) Total FE: Complete (uncond.)	-0.279	-0.201	-0.078	-0.303	-0.232	-0.071
	(0.020)	(0.018)	(0.027)	(0.072)	(0.070)	(0.084)
2nd-choice program (k=2)						
(a) Intention: Enroll	0.165	0.182	-0.017	0.190	0.473	-0.283
	(0.020)	(0.020)	(0.029)	(0.096)	(0.092)	(0.154)
(b) Persistence: Complete ∣ Enroll	-0.281	-0.254	-0.028	-0.268	-0.397	0.129
	(0.023)	(0.023)	(0.032)	(0.076)	(0.079)	(0.112)
(c) Total FE: Complete (uncond.)	-0.116	-0.071	-0.045	-0.078	0.076	-0.154
	(0.023)	(0.024)	(0.033)	(0.076)	(0.074)	(0.104)

Note: (a) Intention: Enroll ($\chi_{ik}(1)FE^{e}_{ik}$) + (b) Persistence: Complete ∣ Enroll ($FE^{\Delta^c}_{ik}e_{ik}$) = (c) Total FE: Complete (uncond., FE^{c}_{ik}). Estimates for marginal applicants are obtained using local quadratic two-stage least squares (2SLS). Robust standard errors are shown in parentheses below the point estimates.

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 to tell us what were your 1st and 2nd choices 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 where to enroll there. What do you think your average grade will be in (you can a scale like upper secondary grades, 1 (worst) - 6 (best))
   (c) your first choice? ☐ grade

i. what is the chance (%) is it that you will get a better grade? ☐ %
(a number from 0 to 100, where 0% is no chance and 100% is certain)

ii. what is the chance (%) is it that you will get a poorer grade? ☐ %
(a number from 0 to 100, where 0% is no chance and 100% is certain)

(d) your second choice ☐ grade

iii. how likely (%) is it that you will get a better grade? ☐ %
(a number from 0 to 100, where 0% is no chance and 100% is certain)

iv. how likely (%) is it that you will get a poorer grade? ☐ %
(a number from 0 to 100, where 0% is no chance and 100% is certain)

6. Suppose you where to enroll there. Of every 100 students, how many do you think would obtain a higher average grade than you?

   in your first choice? ☐ students out of 100

   (e) in your second choice? ☐ students out of 100

7. Suppose you where 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)

8. Suppose you were to graduate from your <u>first choice</u>.

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

   (b) What do you think is the prob that your earnings then will be more than [1.33*(a)]?
   ☐ %

   (c) What do you think is the prob that your earnings then will be less than 0.67*(a)?
   ☐ %
   (a number from 0 to 100, where 0% is no chance and 100% is certain)

9. Suppose you were to graduate from your <u>**second choice**</u>.

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

(b) What do you think is the prob that your earnings at that age will be more than 1.33*(a) in your first job? ☐ %

(c) What do you think is the prob that your earnings at that age will be less than 0.67*(a) in your first job? ☐ %

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

10. 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

    (b) What do you think is the prob that your earnings at that age will be more than 1.33*(a) when you are 45?

    ☐ %

    (c) What do you think is the prob that your earnings at that age will be less than 0.67*(a) when you are 45?

    ☐ %

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

11. 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

    (b) What do you think is the prob that your earnings at that age will be more than 1.33*(a) when you are 45? ☐ %

    (c) What do you think is the prob that your earnings at that age will be less than 0.67*(a) when you are 45? ☐ %

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

12. 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

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

    ☐ %

14. 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

15. 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

16. 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

17. *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:

18. 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

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

    - if [A]

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

        – etc

    - if [B]

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

        – etc

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

    - if [A]

      (c) Do you prefer [A] 1000 NOK with certainty, or [B] 50% chance of winning 185*20=3700 NOK?

        – etc

    - if [B]

      (d) Do you prefer [A] 1000 NOK with certainty, or [B] 50% chance of winning 125*20=2500 NOK?

        – etc